Masters
Program
in **Geospatial**
Technologies

USING GIS TO MAP THE SPATIAL AND TEMPORAL OCCURRENCE OF CHOLERA EPIDEMIC IN CAMEROON

AYUK SALLY AGBOR

Dissertation submitted in partial fulfilment of the requirements for the Degree of *Master of Science in Geospatial Technologies*

UNIVERSIDADE NOVA ISEGI
UNIVERSITAT JAUME·I
WESTFÄLISCHE WILHELMS-UNIVERSITÄT MÜNSTER

USING GIS TO MAP THE SPATIAL AND TEMPORAL OCCURRENCE OF CHOLERA EPIDEMIC IN CAMEROON

Master thesis

Supervised by

Prof. Dr. Ana Cristina Marinho da Costa
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa
Lisbon – Portugal

Co-Supervised by

Prof. Dr. Jorge Mateu
Dept. Lenguajes y Sistemas Informaticos
Professor of Statistics, Department of Mathematics
Universitat Jaume I
Castellón – Spain

Dr. Mark Padgham
Institute for Geoinformatics
Westfälische Wilhelms-Universität Münster
Münster – Germany

February 2014

ACKNOWLEDGMENTS

I am thankful to God Almighty for His abundant grace, glory and strength in my life.

I also acknowledge the joint program at Universidade Nova de Lisboa (ISEGI), Westfälische Wilhelms-Universität Münster (WWU) and Universitat Jaume I de Castellón (UJI) during my period of studies.

I am grateful to my supervisors Prof. Dr. Ana Cristina Costa, Prof. Dr. Jorge Mateu and Dr. Mark Padgham for their patience, contributions, remarks and constructive criticism. Thanks to all my lecturers especially to Prof. Marco Painho for the advice, encouragement and support throughout my studies.

Acknowledging my family for their endless prayers, support and encouragement, special thanks to my precious mum Bate-Manyor Alice Ebai for inspiration, endless prayers, believe and a role model in all aspects of life. I also wish to thank Tabot Samuel, Bate-Manyor Fidelis, Prof. Lambi Cornelius, Dr. Arrey Abangma, Julianna Csatlós, Leonard Lekefua, Angel Asopo, Linus Agwa, Omgba Raphael, James Ndo, Odi Aloysius, Pastor Blaise, Martial Nyendi, Promise Iheme, Binette Fonge, to my younger siblings (Ashu, Chivette, Kelly and Cindy) and to my fallen hero Gideon Ntuma.

Finally I am appreciative to Ivo Abangma for his care and sacrifices throughout my course of studies.

USING GIS TO MAP THE SPATIAL AND TEMPORAL OCCURRENCE OF CHOLERA EPIDEMIC IN CAMEROON

ABSTRACT

Globally, Cholera has been a major infectious disease due to its intercontinental, environmental and cultural factors. This study focused on evaluating the climatic and fresh water proximity factors influencing Cholera epidemic in Cameroon. To this effect, Cholera and climatic datasets in 2004, 2010, 2011 and 2012 to June 2013 were collected and mapped. Both high and low rainfall and temperature extremes were designated as promoters of *V. Cholerae* development and the highest cases were identified in the Littoral, Extreme North and Centre regions. Spatial autocorrelation using Local (Anselin) Moran I on Cholera cases revealed a cluster of Low-Low positive autocorrelation in Adamawa region in 2004, a High-High cluster of positive autocorrelation in the Littoral region and a Low-High negative autocorrelation in the South region in 2012, a Low-High negative autocorrelation in the South West region and a High-Low negative autocorrelation in the North West in 2013. Furthermore, using population numbers to count Cholera cases (prevalence) from 2010 to June 2013, Local Moran I results show a Low-Low cluster of positive autocorrelation in the South region, a Low-High negative autocorrelation in the North region and a High-Low negative autocorrelation in the Adamawa region in 2010, a High-Low negative spatial autocorrelation in the North region in 2011, a High-Low negative spatial autocorrelation in the South region in 2012 and a High-Low negative spatial autocorrelation in the North region in 2013. Spatial Poisson Regression analysis allowed concluding that Average Temperature, Distance to Streams, Population Distribution and Latitude are statistically significant predictors of increased Cholera cases, whereas Average Rainfall and Longitude are significant predictors of lower Cholera cases.

KEYWORDS

Cameroon

Cholera

GIS

Local (Anselin) Moran I

Spatial Poisson Regression analysis

Rainfall

Spatial analysis

Spatial autocorrelation

Temperature

Time series analysis

ACRONYMS

CAMWATER: The Cameroon Water Utilities Corporation

CDC: Centers for Disease Control and Prevention

CFR: Case fatality rate

ESRI: Environmental System Research Institute

GIS: Geographical Information System

GISs: Geographical Information Science

GLM: Generalized linear model

GPS: Global Positioning System

IDW: Inverse Distance Weighting

LISA: Local Indicators of Spatial Association

SARIMA: Autoregressive integrated moving average

UTM: Universal Transverse Mercator

WGS: World Geodetic System

WHO: World Health Organization

TABLE OF CONTENTS

ACKNOWLEDGMENTS..…........iii

ABSTRACT..iv

KEYWORDS………..v

ACRONYMS..vi

TABLE OF CONTENTS………………………………………………….................vii

INDEX OF TABLES……………………………….………........................ix

INDEX OF FIGURES ……………………………………………………...........x

1 INTRODUCTION…………………………………………………………..….1

1.1 Operational definition of terms …………………………………………..…..1
1.2 Background of studies …………………………………………………....…1
1.3 Statement of problem.…………………………………………………..…..3
1.4 Motivation.…………………………………………………………...…..3
1.5 Research hypothesis………………………………………………………..4
1.6 Research questions..……………………………………………………….4
1.7 General objective…….……………………………………………......…5
1.8 General methodology.……………………………………………..…..…5
1.9 Thesis organization.………………………………………………...…6

2 LITERATURE REVIEW………………………………………….............……7

2.1 Cholera and GIS……………………………………………...........…7
2.2 Climate variability on Cholera epidemics……………………………………9
2.3 Cholera and water reservoirs…………………………………................…11

3 STUDY AREA, DATASETS AND DATA PREPARATION……….............…14

3.1 Study area……………………………………………………….….........…14
3.1.1 Location.………………………………………………….................…14
3.1.2 Climate…………………………………………………..........….……15
3.1.3 Relief.……………………………………………………….............….16
3.1.4 Drainage………………………………………………….....…………17
3.1.5 Geology.………………………………………………….........…….…17
3.2 Datasets.………………………………………………………..........….18
3.2.1 Cholera data……………………………………………………...……18
3.2.2 Temperature data……………………………………………...…….…19
3.2.3 Rainfall data…………………………………………………….…..…20
3.2.4 Water reservoir data…………………………………..……..........…22
3.3 Data preparation.…………………………………………….....……22

3.4 Software……………………………………………..……………………23

4 METHODOLOGY………………………………………………….…………24

4.1 Introduction……………………………………………………….............…24
4.2 Data Integration and visualization…………………………...................……25
4.2.1 Mapping and geovisualization……………………………….............……25
4.3 Temporal analysis…………………………………………...…………25
4.4 Spatial analysis…………………………………………..................…25
4.4.1 Inverse Distance Weighting (IDW) ……….………………………...……..25
4.4.2 Proximity analysis …………………………..................................……26
4.5 Autocorrelation analysis……………………….....…….….………………27
4.5.1 Local (Anselin) Moran I statistic…………………………….............……27
4.6 Spatial Poisson Regression analysis…..………………………........………29

5 RESULTS AND ANALYSIS…………………………………….............…30

5.1 Mapping and geovisualization (Choropleth mapping)...................................30
5.1.1 Population distribution in Cameroon...30
5.1.2 Count Cholera cases in Cameroon...31
5.1.3 Count Cholera deaths in Cameroon...32
5.2 Inverse Distance Weighting (IDW)…………………………….……….........34
5.2.1 Interpolated rainfall surface during the rainy and dry season in Cameroon...34
5.2.2 Interpolated temperature surface during the rainy and dry season in Cameroon………………………………………………………………………35
5.3 Time series analysis……………………..…..…35
5.4. Local (Anselin) Moran I statistic………………....……………………..……36
5.4.1 Local Moran I statistic on count Cholera cases in 2004.................................37
5.4.2 Local Moran I statistic on count Cholera deaths in 2004...............................38
5.4.3 Local Moran I statistic on count Cholera cases and deaths in 2010...............39
5.4.4 Local Moran I statistic on count Cholera cases and deaths in 2011...............40
5.4.5 Local Moran I statistic on count Cholera cases in 2012.................................40
5.4.6 Local Moran I statistic on count Cholera deaths in 2012...............................41
5.4.7 Local Moran I statistic on count Cholera cases in 2013.................................42
5.4.8 Local Moran I statistic on count Cholera deaths in 2013...............................43
5.4.9 Local Moran I statistic of prevalence in 2010..44
5.4.10 Local Moran I statistic of prevalence in 2011..45
5.4.11 Local Moran I statistic of prevalence in 2012..46
5.4.12 Local Moran I statistic of prevalence in 2013..47
5.5 Spatial Poisson Regression analysis..49

6 CONCLUSIONS AND RECOMMENDATIONS..52

6.1 Conclusions…………..…………………………...............………..……..52
6.2 Limitations of the study…………………………......................................55
6.3 Future studies ……………………………….......................................56

BIBLIOGRAPHIC REFERENCES………………………….………………............57

INDEX OF TABLES

Table 1: Collection stations with mean, minimum and maximum temperatures in Cameroon……………….…...........................……………………….....................20

Table 2: Collection stations with mean, minimum and maximum rainfall in Cameroon………………….............................…………………….......................21

Table 3: Proximity of the ten main cities (centroids) to water reservoirs in Cameroon………..…………................……………………......................................26

Table 4: LISA and related statistics ……………………….....................................48

Table 5: Variables for Spatial Poisson Regression analysis.......................................49

Table 6: Spatial Poisson Regression of total Cholera cases in 2004, 2010, 2011 and 2012 to June 2013..50

Table 7: Spatial Poisson Regression of total Cholera deaths in 2004, 2010, 2011 and 2012 to June 2013..51

INDEX OF FIGURES

Figure 1: Gilbert's recreation of Snow's dot-map (McLeod, 2000)………..…………2

Figure 2: Location map of Cameroon……………………………………....………14

Figure 3: Drainage map of Cameroon……………………………………..……..…17

Figure 4: Cholera collection points in Cameroon (2004, 2010, 2011 and 2012 June 2013)……………………………………………………………………….……..19

Figure 5: Meteorological stations of Temperature and Rainfall……………..……...22

Figure 6: Flow diagram of research methodology……………………………..……24

Figure 7: Population distribution in Cameroon from 2010 to June 2013……..…….31

Figure 8: Count Cholera cases in 2004, 2010, 2011 and 2012 to June 2013 in Cameroon……………………………………………………………………………32

Figure 9: Count Cholera deaths in 2004, 2010, 2011 and 2012 to June 2013 in Cameroon……………………………………………………………………………33

Figure 10: IDW Interpolated rainfall surface during the rainy (left) and dry (right) season in Cameroon…...34

Figure 11: IDW Interpolated temperature surface during the rainy (left) and dry (right) season in Cameroon…………………………….…………..…..…35

Figure 12: Time series analysis of Cholera cases (a) and deaths (b) in Cameroon....36

Figure 13: Local Moran I statistic of Cholera cases in 2004 in Cameroon………....37

Figure 14: Local Moran I statistic of Cholera deaths in 2004 in Cameroon ……....38

Figure 15: Local Moran I statistic of Cholera cases and deaths in 2010 in Cameroon……………………………………………………………..…..39

Figure 16: Local Moran I statistic of Cholera cases and deaths in 2011 in Cameroon…………………………………………………………..……..40

Figure 17: Local Moran I statistic of Cholera cases in 2012 in Cameroon………....41

Figure 18: Local Moran I statistic of Cholera deaths in 2012 in Cameroon…..……42

Figure 19: Local Moran I statistic of Cholera cases in 2013 in Cameroon………...43

Figure 20: Local Moran I statistic of Cholera deaths in 2013 in Cameroon…..……44

Figure 21: Local Moran I statistic of prevalence in 2010 in Cameroon……..…...45

Figure 22: Local Moran I statistic of prevalence in 2011 in Cameroon……..…...46

Figure 23: Local Moran I statistic of prevalence in 2012 in Cameroon……..…...47

Figure 24: Local Moran I statistic of prevalence in 2013 in Cameroon………….....48

1. INTRODUCTION

1.1 Operational Definition of Terms

Cholera is an acute enteric infection caused by the ingestion of bacterium *Vibrio Cholerae* present in faecally contaminated water or food. Primarily linked to insufficient access to safe water and proper sanitation, its impact can be even more dramatic in areas where basic environmental infrastructures are disrupted or have been destroyed (WHO, 2013).

Cholera is also defined as an acute intestinal infection characterized by severe diarrhea, cramp, caused by ingestion of water or food contaminated with the bacterium Vibrio comma, (Also called) Asiatic Cholera, epidemic Cholera, Indian Cholera (Collins English Dictionary, 2000).

Epidemic refers to an increase, often sudden, in the number of cases of a disease above what is normally expected in that population in that area (CDC, 2012).

An epidemic is defined as an increase in the frequency of occurrence of a disease in a population above its baseline or expected level in a given period. The term is used broadly and the number of cases and time period are often unspecified (Barratt, 2009).

1.2 Background of Studies

Vibrio Cholerae (*V. Cholerae*) is a Gram-negative, comma-shaped bacterium. Some strains of *V. Cholerae* cause the disease Cholera. *V. Cholerae* is facultatively anaerobic and has a flagellum at one cell pole. It was first isolated as the cause of Cholera by Italian anatomist Filippo Pacini in 1854, but his discovery was not widely known until Robert Koch, working independently 30 years later, publicized the knowledge and the means of fighting the disease. There are estimated 3–5 million Cholera cases and 100,000–120,000 deaths due to Cholera worldwide every year and up to 80% of cases can be successfully treated with oral rehydration salts (WHO, 2012). There are two serogroups of *V. Cholerae* which are O1 and O139. *V. Cholerae* O1 causes the majority of outbreaks, while O139 was first identified in Bangladesh in 1992 and is confined to South-East Asia and the non-O1 and non-

O139 *V. Cholerae* can cause mild diarrhea but do not generate epidemics (WHO, 2012). The number of Cholera cases reported to the World Health Organization (WHO, 2012) continues to rise. For 2011 alone, a total of 589,854 cases were notified from 58 countries, including 7816 deaths. Many more cases were unaccounted for due to limitations in surveillance systems and fear of trade and travel sanctions. There has been multidisciplinary approach based on prevention, preparedness and response, because Cholera is caused mostly by untreated drinking water and the collection of water from open water source, contaminated food and shell fish, environmental factors like refuse dumps and climatic factor like temperature, rainfall and humidity (Sasaki et al. (2008); Chingayipe (2008); Gaffga et al. (2007)).

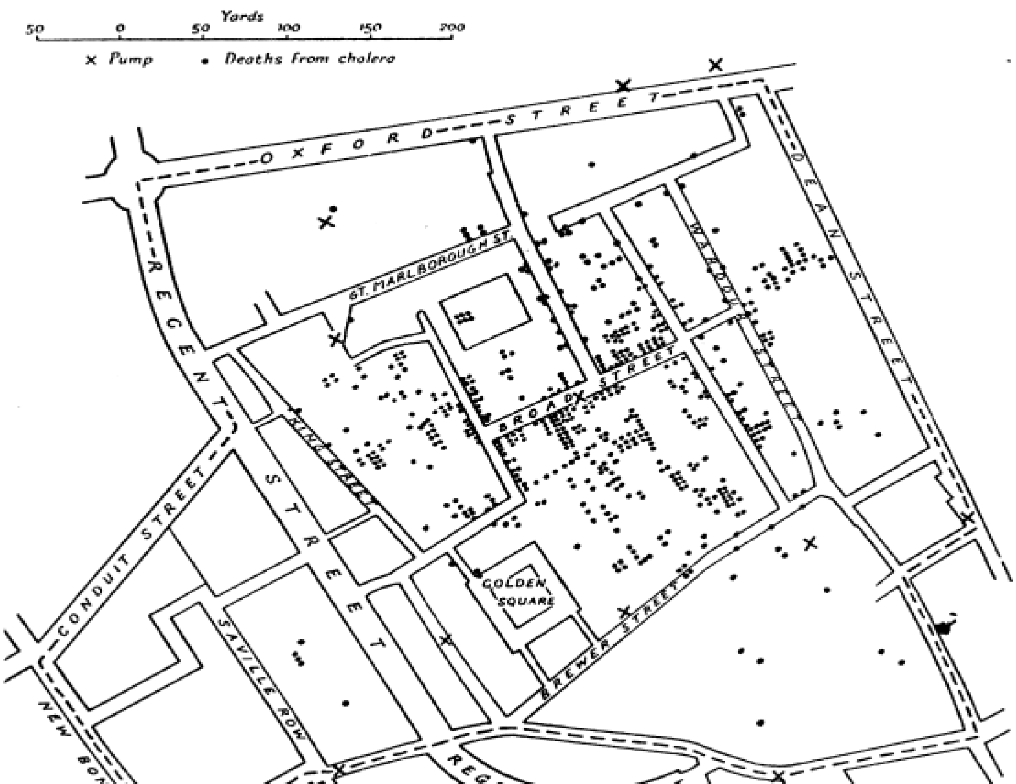


Figure 1: Gilbert's recreation of Snow's dot-map
Source: McLeod (2000)

Geographic information systems (GIS) or increasingly geographic information science (GISs) has been used in the analysis of public health since 1854 when John

Snow used a hand-drawn map to analyze the geographic locations of deaths during the Cholera outbreak in London which shows the locations of the 11 pumps, and Cholera deaths by home addresses, marked as black points stacked perpendicular to the streets (Figure 1) and is widely regarded as data visualization's power. The analysis done by John Snow provides indications on the benefits of GIS on Cholera epidemics as the modern problems of Cholera today are more larger in scope than the London Cholera epidemic in 1854, researchers now depend more on GIS, spatial analysis and computational systems in order to be able to collect, store, predict and for successful analysis of Cholera epidemics around the world.

1.3 Statement of the Problem

Cholera epidemic is catastrophic because it causes death. The global experience on the occurrence of Cholera epidemic can be introduced into any country and even any community, but problems can only be created in areas where other acute enteric infections are endemic, that is in areas where sanitation is deficient. The disease has been a constant health burden in Cameroon since 1971 when 2167 Cholera cases (Minister of Public Health, Cameroon) were reported.

1. Cholera is a complex health problem to manage because of a combination of factors. These vary from biophysical to social and economic, including overcrowding, urbanization, proximity to contaminated water sources and the density and proximity of refuse dumps.
2. Cameroon, just like any other area in the world, faces issues related to frequent Cholera outbreaks throughout the years which led to many deaths.
3. Assessing the risk of an outbreak based on environmental preconditions, climatic variability and the role of the government is very important.

It is therefore the rationale of this study to investigate the issues raised above, and examine how they affect development and human health in Cameroon.

1.4 Motivation

The successive outbreaks of Cholera that affected Cameroon from 1971 to June 2013 motivated the study of this disease. Cameroon is a land of natural differences within its ten regions with all the major climates and vegetation making it difficult to have a unique and single cause within the country. There is also the role of hydrology in Cholera, due to the fact that both droughts and floods are followed by Cholera epidemics as water scarcity causes Cholera in the dry season, while water abundance causes Cholera in the raining season. There is lack of purification of public water system in Cameroon especially in the rural areas due to the use of community pipeline network and direct consumption of fresh water. The corrupt nature of the officials in Cameroon has caused great hindrance to portable water supply due to embezzlement of funds allocated for the maintenance of portable water supplies. The diversity in cultures and languages of Cameroon is a barrier to workers of the public water sector (CAMWATER). There is evidence that the disease is most common in urban areas (high Cholera count cases in Douala) of Cameroon with poor sanitation, urban sprawl, and congestion (Minister of Public Health, Cameroon). Raw or undercooked fish and seafood caught in waters polluted with sewage carries the bacterium that causes Cholera. Satellite images and digitized waterbodies can be used to enhance the mapping and proximity of environmental factors associated with Cholera epidemic. Spatial statistics and the integration of geographic information systems (GIS), while also performing temporal analysis, will provide public health officials with the vital information needed to detect, collect affected numbers and manage outbreaks.

1.5 Research hypothesis

1. "There is a correlation between Cholera over time and climatic variations conditions which might promote plankton growth and *V. Cholerae* multiplication within the ten regions of Cameroon".
2. The spatial distribution of Cholera cases is not homogeneous in the study region.
3. GIS and spatial statistics can be used to assess the proximity of environmental factors associated with Cholera epidemic.

1.6 Research questions

1. "Are there higher risk of Cholera in some regions?"
2. "What are the underlying risk factors?"

3. “Is there underreporting of Cholera by region and by year?”
4. “Does Cholera turn to occur in proximity to each region and is there a level of clustering around a particular region?”
5. “Can the proximity distance to the nearest waterbodies influence pollution?”

1.7 General objective

The main objective is to identify and characterize the spatial and temporal distribution of Cholera, climatic factors and proximity to water sources that influences the risk of infection in Cameroon using GIS. The specific objectives are:

1. To examine health problems such as Cholera as a consequence of climate variability.
2. To investigate the patterns of Cholera cases and deaths over time in 2004, 2010, 2011 and 2012 to June 2013.
3. To map potential Cholera causing factors such as water reservoirs in Cameroon using GIS.
4. To outline and propose possible solutions to the effects of Cholera Epidemics (based on epidemiological data) for future health analysis and for health officials and policy makers.

1.8 General methodology

The methodology of interest will be:

1. Applying time series analysis by using weekly epidemiological data of reported Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013.
2. Compute Moran I statistic for Cholera using epidemiological data for the ten regions of Cameroon.
3. Poisson Regression analysis to determine the most important environmental factors that can predict/related to the presence of Cholera.
4. Evaluation of spatial patterns for analyzing by landscape and by distance within the ten regions of Cameroon.

1.9 Thesis organization

This thesis will focus on Cholera data retrieved from the Ministry of Public Health in Cameroon, rainfall and temperature from the National Institute of Cartography, Department of Transport in Cameroon and proximity to water reservoir obtained from digitizing water lines. GIS will be used in the spatial interpolation, temporal (time-series), spatial autocorrelation (Local Moran I) and Poisson Regression analyses to map Cholera disease in Cameroon. The thesis comprises of six chapters:

Chapter 1 – Introduction

This chapter contains the operational definition of terms, background of studies, statement of the problem, motivation, research hypothesis, research questions, general objective and general methodology for Cholera epidemic in Cameroon.

Chapter 2 – Literature Review

This chapter focuses on the application of GIS on Cholera epidemics studies, climate variability and water reservoirs.

Chapter 3 – Study Area, Datasets and Data Preparation

This chapter contains the location, climate, geology, relief, and drainage of Cameroon, description of data sources, software and data preparation.

Chapter 4 – Methodology

This chapter describes the data collection techniques, methods and tools applied to the study. Data Integration and visualization, proximity analysis, mapping and geovisualization, autocorrelation analysis (Local Moran I statistic) and Spatial Poisson Regression analysis of Cholera distribution within the ten regions of Cameroon are analyzed.

Chapter 5 – Results and analysis

This chapter aims to determine and represent data Integration and visualization, mapping and geovisualization, autocorrelation analysis (Local Moran I statistic) and Spatial Poisson Regression analysis of Cholera epidemic using GIS.

Chapter 6 – Conclusions and recommendations

This chapter presents a summary on the conclusions, limitations of the study and offers recommendations for future studies on Cholera epidemic in Cameroon.

2. LITERATURE REVIEW

The application of GIS and the emerging free software providing access to satellite imagery is becoming increasingly used in public health analysis which originated from the analysis of a hand drawn map of London in 1854 by John Snow (physician). Richards et al. (1999) anticipated the use of GIS in the future mapping of public health data in the 21st century as communities will be able to collect health information from a variety of different data sources and recognize spatial patterns stating that the greatest strength of GIS is that its product is a map. Lozano-Fuentes et al. (2008) indicates the use of Google Earth™ to strengthen public health capacity utilizing GIS technology to support management of vector-borne diseases. Furthermore Scotch et al. (2006) explored the role of GIS during community health assessment problem solving, to analyze health and population data and perform numerical-spatial problem solving on how public health professionals integrate software during typical problem solving scenarios.

Krieger et al. (2001), is still not certain about the evaluation and accuracy of using Geocoding in public health research, but Boulos (2005) is introducing the health GIS community to the emerging online consumer geoinformatics services through the creation of interactive map using Google Maps API, Google Earth KML, and MSN Virtual Earth Map Control using health data. Nevertheless, GIS has now been widely used in public health analysis, especially Cholera in the recent years.

2.1 Cholera and GIS

Investigating the geographical patterns of Cholera in Mexico during 1991 to 1996 was Borroto et al. (2000), during the seventh Cholera pandemic. By using the cases of Cholera incidence and population database obtained from the 1990 population census of Mexico, 32 states were classified into five strata to obtain their cumulative incidence rate with a cut off point for each interval in order to determine the natural breaks being done with the use of GIS MapInfo professional for windows. Also Moran I analysis was used to compute patterns of spatial clustering of states with similar cumulative incidence rates. The result was a positive and statistical significant spatial autocorrelation which reflects a north-south gradient and also a spatial clustering of Southern states with high incident rates due to high poverty level, low urbanization and as a result of their geographic location.

Mayala et al. (2003), worked on the mapping of Cholera epidemic prone areas in Ilala districts (22 wards) in Tanzania, to determine the predisposing factors of Cholera using GIS. During this study a database to store all spatial and non-spatial data sources (digital maps, population distribution maps, and water distribution per ward, which include water supply sources were obtained) and the location of health centres were done by the use of the Global Positioning System (GPS). ArcView GIS was used to display all data and an observation of low lying areas of Buguruni, Vingunguti and Mchikichini, which experienced flooding during the rainy season were frequently susceptible to Cholera than the other areas in Ilala and also, large numbers of Cholera cases were observed in area characterized by shallow wells.

In the spatial analysis of risk factor of Cholera Outbreak for 2003-2004 in a Peri-Urban area of Lusaka, Zambia, 6542 cases with 187 deaths were reported by Sasaki et al. (2008), who discussed the mode of Cholera transmission and risk factors. This study used Geographic Information System (GIS) by the utilization of Lusaka's digital base map based on satellite imagery, the creation of Voronoi diagram of 125 water points and matched case-control method. It was concluded that Cholera has a strong association to the lack of latrine and drainage systems and suggested that chlorination of portable water and hand washing could further reduce cases and increase the conditions of daily life.

Osei et al. (2008) conducted research on the spatial dependency of *V. Cholerae* prevalence on open space refuse dumps in Kumasi, Ghana using statistical modeling due to the persistence of Cholera epidemic from 1995 to 2005, which reported a total of 26,924 cases and 620 deaths to the WHO. The studies suggest that *V. Cholerae* needs an aquatic environment to survive and its ability to survive within and outside that environment makes it a complex health problem. This research also focused on proximity and density to refuse dumps, in the urban city of Kumasi which resulted to a direct relationship and spatial dependency of Cholera prevalence and refuse dumps. Osei (2010) examined the case of Cholera epidemiology in Ghana, due to its increasing number of occurrence in the African continent. Spatial and temporal investigation were conducted, proxies for refuse dumps and environmental sanitation as well as surface water pollution as location for Cholera transmission. Using satellite and Bayesian semi-parametric regression approach with the space time diffusion pattern, factors like urbanization, migration and overcrowding were isolated as the main influence of Cholera.

Shittu et al. (2010) used GIS-supported software to investigate Cholera outbreaks in Abeokuta in Nigeria during the period of 20th November, 2005 to 1st of January, 2006. Statistical significant test and the relative risk for estimated odd ratio of incidence for exposed drinking water consumption sources was conducted together with the use of EpiTnfor 6.0 to analysis of epidemiological data in Abeokuta. The results from the McNemar's Chi square significant testing showed that the population that consumed municipal tap water had 10 times higher risk than those who consumed sachet water produced in that same municipal area during the period of the outbreak. A post epidemiological environmental investigation showed a progressive contamination of municipal water along its distribution points.

According to Fernandez et al. (2012), Cholera is prominent in areas characterized by urban sprawl in most African countries where clean water is a challenge. Working with the Harare area of Zimbabwe, spatial analysis which aimed at getting the relationship between the distribution of Cholera cases and topographic elevation was conducted. Also an ecological study area was developed and GIS was used to illustrate the Cholera cases and average elevation by suburbs. A Bayesian approach was conducted to model the relationship between elevation in meters in Harare and the risk of Cholera. This study resulted to a Cholera risk of 30% lower for a 100 meters increase in topographical elevation. Spatial patterns of Cholera distribution was characterized by a lower Cholera risk in the highest elevation zones in the suburbs of Harare in Zimbabwe.

2.2 Climate variability on Cholera epidemics

According to Lipp et al. (2002) Cholera has a historical context that links to specific seasons and biogeographical zones. This paper is on the effect of global climate on Cholera by analyzing the frequency of specific disease cases throughout the year and concluded that *V. Cholerae* has long been known as a fecal-oral pathogen and indeed infection rates are significantly greater in areas with poor sanitation. According to Gaffga et al. (2007), Cholera was being eliminated from developed countries through water and sewage treatments and now it remains a major source of mortality in developing countries especially in Africa, indicating that the control of Cholera in Sub-Saharan Africa will be a reached effort of the Millennium Development Goals.

Chingayipe (2008) did studies on the "factors affecting Cholera case detection by the communities in Chiradzulu district Malawi", which revealed that Cholera cases are more occurrent in the rainy season with high case fatality rates of 4.5 causing panics to the community. Qualitative and quantitative methods were conducted to access the symptoms while taking into consideration the distances from the main hospitals and associated cultural beliefs were the main factors of Cholera spread. Traerup et al. (2010) focused on the health impacts of climate change on Cholera in Tanzania, revealing a significant relationship of Cholera with environmental factors and how this relationship can be used to predict climate change. This result was used to give an estimate on Cholera and climate change in Tanzania by 2030, which reveals the cases of Cholera exceeding the preventive cost measures.

Piarroux et al. (2010), viewed on the respective roles of environment strain changes and human driven dissemination during the Cholera epidemics in 2010 around Lake Chad Basin, east Africa and Haiti which experienced 476,714 recorded cases and 6648 count deaths as on October 18th 2011 and envisaged the environment plays a major role in the transmission of Cholera though there are difficulties in predicting the evolution of Cholera. A time series analysis by Reyburn et al. (2011) on climatic variability and the outbreaks of Cholera in Zanzibar, East Africa examined the impact of Ocean and climatic factors of Cholera using seasonal autoregressive integrated moving average (SARIMA) model. The result was a positive association of Cholera to temperature and rainfall, which may be applied to forecast the outbreak of Cholera.

Kometa et al. (2012) researched on human health vulnerability to climate variability on Cholera and meningitis in the Far North region of Cameroon, which found vector-borne diseases as the main effect on human health especially Cholera and indicating the issue of poor sanitation, poor waste disposal and management as major contributing factors by using primary sources like questionnaires and secondary sources from epidemiologic, climate, ecologic and socio-economic data. Bompangue et al. (2012) focused on the re-emergence of Cholera in Kinshasa after a ten-year hiatus (from 2001). Surveillance data was used to map the spatio-temporal progress of Cholera cases while comparing the spatial distribution with previous epidemic in 1996 and 2001 in Kinshasa. Correlation and regression analysis was done to assess the impact of rainfall that show a correlation with case counts and population densities involved in fishing and trade.

2.3 Cholera and water reservoirs

Shapiro et al. (1999) did one of the earlier researches on environmental reservoir for Cholera from Lake Victoria in Kenya due to the fact that Sub-Saharan Africa had the highest reported Cholera incidence and from the 1997 Cholera epidemic in Western Kenya, which resulted to 547 deaths (case fatality rate was 4%). Case control studies, laboratory testing and multivariate analysis were conducted to determine that sharing of meals with watery diarrhea infected persons and during funeral (death) ceremonies were the main transmission modes.

According to Emch et al. (2008), environmental factors are the causes of Cholera and can be used for prediction as researched in the case of Bangladesh and Vietnam. Environmental factors were derived from satellite imagery, sea surface temperature and sea surface height, which were combined with in-situ variables of rainfall, temperature and river discharge/height to perform time series data. The result shows the sea surface temperature as the most influential factor for Cholera in Hue, Vietnam whereas increases in ocean chlorophyll concentrations are highly related to the increase of Cholera magnitude in Bangladesh.

According to Magny et al. (2008) there are environmental signatures associated with Cholera epidemics as *V. Cholerae* is autochthonous to estuarine, riverine and coastal waters. Stating that temperature, salinity and rainfall are vital factors in the ecology of *V. Cholerae* as humans who rely on untreated drinking water are mostly affected. This study analyzed the outbreak of Cholera during 1998-2006 in Kolkata, India and

Bangladesh using earth observation with the objective of developing a prediction model. The results gave a relationship between the time series observations for Cholera in Kolkata, India and chlorophyll concentration (CHL) with rainfall anomalies, thus ocean and climate patterns are useful predictors of Cholera epidemics.

Shultz et al. (2009) investigated on Cholera Outbreak in the Kenyan refugee camp in Kakuma, which was struck by watery diarrhea in April of 2005 were 418 people were treated and had a devastating effect of 4 deaths. A case-study control and a multivariate model was used, which resulted to proper water storage containers as the matched odds ratio [MOR] was equals to 0.49 [0.25, 0.96] as most refugee camps are more vulnerable to Cholera due to poor sanitation, overcrowding and constrains to portable water supply. Jutla et al. (2011) researched on warming oceans, phytoplankton and river discharge for Cholera outbreaks on the Brahmaputra, Orinoco, Congo and Amazon rivers. The role of terrestrial nutrients was examined and concluded that sea surface temperature (SST) has a positive relation with phytoplankton blooms, which during warming climates causes Cholera outbreaks.

Frerichs, R. R. (2013) reported on the epilogue of the origin of Cholera in Haiti, which resulted from January 2, 2010 earthquake that led to 515,699 cases and 6,942 deaths in November 30, 2011. He wrote about the emergence and impact of Cholera in Haiti as the modern "John Snow". Previous hypothesis on studies conducted have been generated, linking water sources as the main mode of transmission due to the fact that river bathing and drinking water consumption are common practices and the climatic hypothesis which visualize *V. Cholerae* as an aquatic bacterium, which lies dormant in the coastal waters, which if disturbed can lead to infections and Cholera outbreaks.

Previous studies to use GIS by Sasaki et al. (2008), satellite imagery and proximity to refuse dump by Osei (2010) and using environmental factors to analysis Cholera epidemic is relevant to my scientific aims while understanding the origin and transmission route of Cholera by Nyamogoba et al. (2002), creating a database to store all spatial and non-spatial datasets, including the use of GPS to map all available health centre locations by Mayala et al. (2003), expanding studies on river bathing and drinking water consumption especially in developing countries by Frerichs, R. R. (2003) are studies that are worth repeating.

Studies by Kometa et al. (2012) which used questionnaires seems not so good as the studies was conducted in areas with high illiteracy rates. Furthermore Shapiro et al. (1999) did a case control studies on the sharing of meals during funeral studies also seem not so good as the focus of studies should be based more on the drinking water source although poor sanitation can also influence Cholera outbreaks.

In conclusion, Cholera can be seen to be influenced from a diversity of factors as Njoh, E. M. (2010), investigated Cholera epidemic and barriers to healthy hygiene and sanitation in Cameroon, which resulted to the conclusion that impure water, low socio-economic status and poor sanitation are the major transmitting factors of Cholera, highlighting other contributing factors like human behavior and practices which are cultural in nature. Mahamud et al. (2012) wrote about the importance of sanitation and soap to fight Cholera epidemic in Kakuma refugee camp in Kenya as a case-study control method was conducted with the help of questionnaires and hospital registry. Therefore using GIS techniques to combine Cholera datasets to climatic variables and proximity to water reservoirs can be used in the future prediction of Cholera epidemics.

3. STUDY AREA, DATASETS AND DATA PREPARATION

3.1 Study Area

3.1.1 Location

Cameroon, officially called the Republic of Cameroon (French: République du Cameroun), lies midway between West and Central Africa. It stretches from the Gulf of Guinea in the South-West to Lake Chad in the North and lies approximate between 11^{o} of (attribute (01^{o} 80f – 13^{o}00f N) and 08^{o} longitude (08^{o} 251-Yaoundé, 2008 216^{o}20f E). It is bounded to the South-West and West by the Gulf of Guinea (the Atlantic Ocean) and the federal Republic of Nigeria respectively (Figure 2).

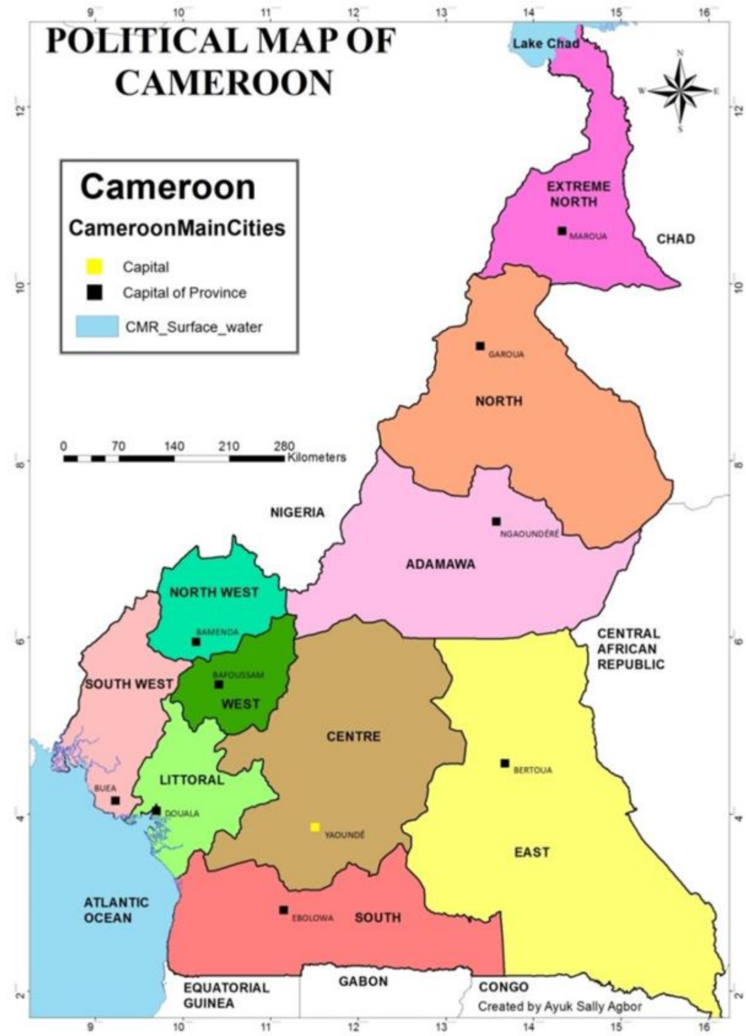


Figure 2: Location map of Cameroon
Source: Author

Cameroon is bordered to the North by Lake Chad, North-East and East by the Republics of Chad and Central Africa respectively, and South by the Republics of Congo, Gabon and Equatorial Guinea (Ministry of Mines and Geology, 2009). Cameroon's coastline lies on the Bight of Bonny, part of the Gulf of Guinea and the Atlantic Ocean. The country is divided into 10 semi-autonomous regions and 58 divisions and the largest city is Douala (WHO, 2012). At 183,568 square miles (475,440 km2) and a (coastline of 402km), Cameroon is the world's 53rd largest country. It is comparable in size to Papua New Guinea, and somewhat larger than the U.S. State of California. Cameroon's landmass is 181,252 square miles (469,440 km2), with 2,317 square miles (6,000 km2) of water. Cameroon is sometimes described as "Africa in miniature" because it exhibits all the major climates and vegetation of the continent: mountains, desert, rain forest, savanna grassland, and ocean coastland. Cameroon can be divided into five geographic zones and these are distinguished by dominant physical, climatic, and vegetative features. The capital of Cameroon is Yaoundé (population in Yaoundé: 1'430'000 in 2005) and the 10 regions of Cameroon are: Adamawa, Centre, East, Extreme North, Littoral, North, North-West, South, West and South West, which can be visualized in (Figure 2).

3.1.2 Climate

The Republic of Cameroon is found respectively in the intertropical zone but the climate is however not limited. Cameroon extends from latitude 2^{o} to 13^{o} north of the Equator. This location gives the country almost all the characteristic of the Equatorial climates, which include generally hot, rainy and dry condition. The equatorial climate is found in the Southern part of the country up to latitude 0^{o}N and the tropical climate between 0^{o} and 13^{o}N (Neba, 1999). Cameroon like most countries in the equatorial zone is a hot country with its average yearly temperatures varying from 20^{o} to 28^{o}C. In Cameroon, the temperatures and temperature changes increase as one move from the South and the coast towards the North. In the Southern part of the country, temperatures remain relatively constant; the temperature ranges in the North are much greater than the south. Insolation is much greater in the North where the climate is hotter and dryer than in the South as the reduced insolation in the South is caused by more cloudy skies, greater precipitation and higher relative humidity (Neba, 1999).

Rainfall reduces from the coast of Cameroon toward the North and interior of the country. Highland areas receive more rainfall than areas of low altitude and relative humidity also varies in the same order as rainfall, being greater in the coast than in the hinterland. Cameroon has four distinct seasons in the Southern and Central regions; the long dry season at the beginning of the year, the long wet season from September to December, the short dry season in August and the short wet season between the months of March and June. The North which begins from the Adamawa to Lake Chad has two distinct seasons; a dry season from November to April and a wet season from May to October (Neba, 1999).

3.1.3 Relief

The relief of Cameroon can be divided into northern, southern and western geographical regions. North of the Benue River, the savanna plain that occupies the country's centre declines in elevation as it approaches the Lake Chad basin. The region contains scattered inselbergs, mounds of erosion-resistant rock that rise above the plains. The Gotel Mountains of the Adamawa Plateau trend from south to north, culminating in the Mandara Mountains of the northwest. The central region extends east from the western highlands and from the Sanaga River north to the Benue River. The land rises progressively to the North and includes the Adamawa Plateau, with elevation between 2,450 and 4,450 feet (750 and 1350 metres).

The southern region extends from the Sanaga River to the southern border and from the coast eastwards to the Central African Republic and the Republic of Congo. It consists of coastal plains that are about 25 miles (40km) wide and a densely forested plateau with an average elevation of a little more than 2,000 feet (600 metres). The western region extends north and west from the Sanaga River and continues north along the Nigerian border as far as the Benue River. The relief is mostly mountainous as a result of a volcanic rift that extends northward from the islands of Bioko. Near the coast, the active volcanic Mount Cameroon rises to the highest elevation in western Africa with 13,435 feet (4,095 metres).

3.1.4 Drainage

The rivers of Cameroon form four large drainage systems. In the South the Sanaga, Wouri, Nyong and Ntem rivers drains to the Atlantic Ocean. The Benue River and its tributary and the Kèbi, flow into the Niger River basin of Nigeria. The Logone and Chari rivers which form part of the eastern border with Chad drains into Lake Chad and the Dja River joins the Sanaga River and flows into the Congo River basin (Figure 3).

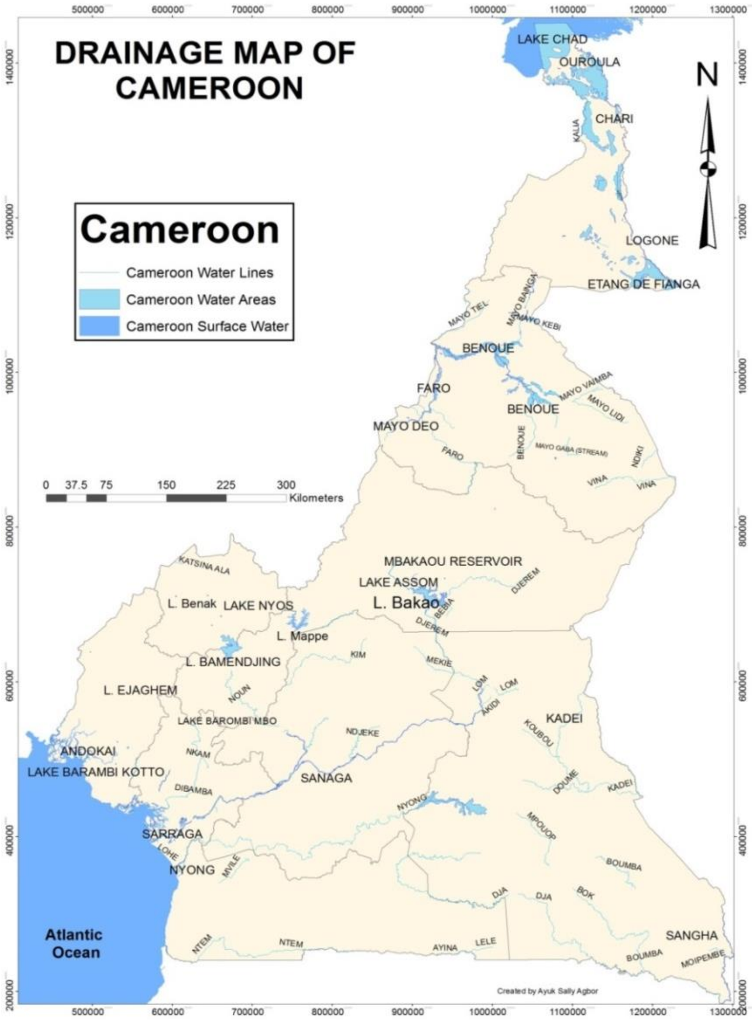


Figure 3: Drainage map of Cameroon
Source: Author

3.1.5 Geology

Cameroon’s geological history begins with the Achaean era between 3.5 and 2.5 billion years ago (Ministry in charge of Mines and Geology, 2009). Four- fifth of the geology of Cameroon is composed essentially of hard crystalline rocks which form the bed rock. This bed rock is covered on the surface in certain zones either as sedimentary materials or volcanic soils (Neba, 1999). The geology of Cameroon is composed of several tectonic units, which consist of the craton, situated at the extreme south parts of the country; it is called the Ntem formations and comprises charnockites, leptynites, gneiss and granodiorites. The craton cover (proterozoic) is located in the southeast of Cameroon on the border of Central African Republic and Congo. The Pan-African chain covers the greater part of the territory and its formation have been put in place during the orogeny of the whole continent of Africa and the Quaternary (Far North in the Logone - Birni) is related to the sedimentation of the Lake Chad (Ministry in charge of Mines and Geology, 2009).

3.2 Datasets

3.2.1 Cholera data

The Cholera data used for this project was obtained from the Ministry of Public Health in Cameroon. The Ministry of Public Health simply recorded every Cholera case weekly in all affected areas which was organized to represent the ten regions of Cameroon (Far North, North, Adamawa, Centre, East, West, South, South West, Littoral and North West). The Cholera data collected was from 1971 to June 2013 and only the datasets in 2004, 2010, 2011 and 2012 to June 2013 were used in this study. Cameroon first reported Cholera cases in 1971 when the current pandemic hit the African continent of which 2167 cases were reported in 1971 with a high case fatality rate (CFR) of 15%. In 1985, 1158 cases were notified with a CFR close to 9%. In 1991, Cameroon reported 4026 cases with a CFR of 12%, and in 1996 the country reported 5912 cases and 494 deaths with a CFR of 8.4%.

A large outbreak occurred in 2004, when 8005 cases were reported in West, East, Centre, Littoral, Far North, South and South West regions. In 2005, Cameroon reported 2847 cases including 110 deaths (CFR 3.9%) with 70% of the cases from the Littoral region (2136 cases). In 2006, Cameroon reported 922 cases including 35 deaths (CFR 3.8%). A first outbreak occurred from April to June in Bafoussam (West province) and a second one occurred in the Far North region from November, 2009 until end of 2011. In 2009, Cameroon reported 333 cases and 43 deaths, in 2010, 7240 cases were reported and 480 deaths and in 2011, 23,152 cases were reported and 843 deaths. From 1971 to June 2013, 77152 Cholera cases and 3788 deaths have been reported in Cameroon. Furthermore there were 43736 cases and 1749 deaths specified for the ten regions while 33416 cases and 2039 deaths were not specified to any particular region. Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013 location points in Cameroon are represented in Figure 4.

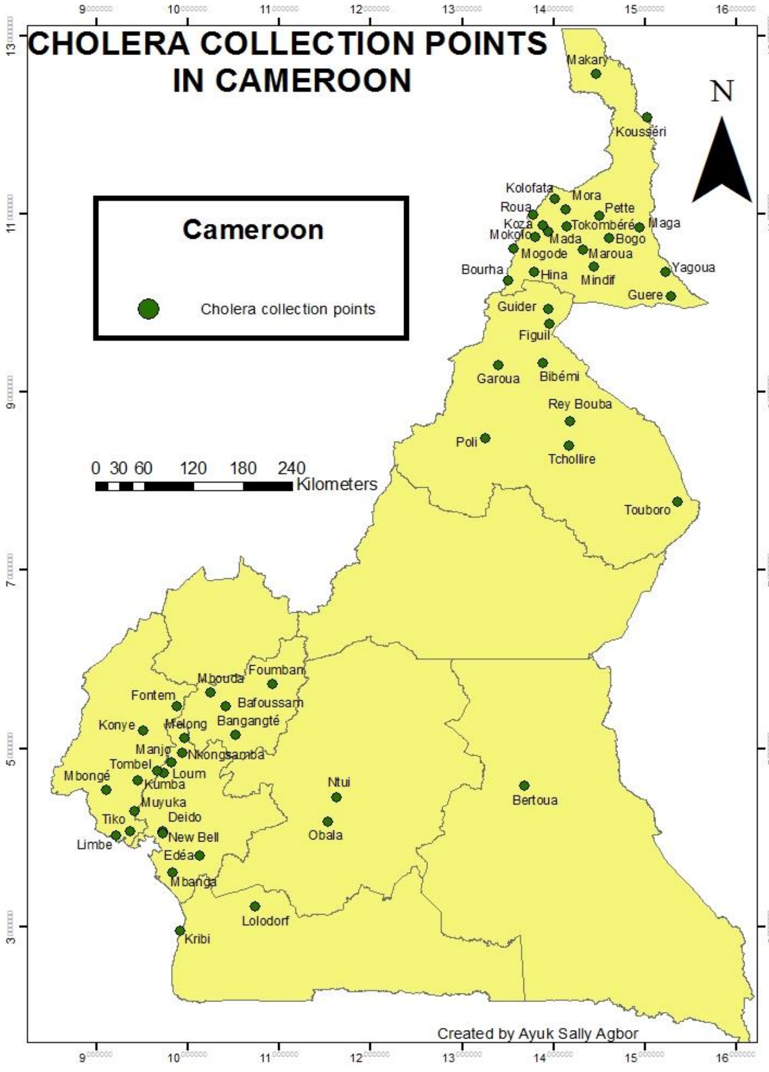


Figure 4: Cholera collection points in Cameroon (2004, 2010, 2011 and 2012 to June 2013)
Source: Author

3.2.2 Temperature data

Temperature data for the Republic of Cameroon were collected from the Department of Transport, branch of the National Institute of Cartography in Yaoundé. Monthly temperatures were collected in degrees Celsius and 1/10 unit measurements for the ten regions of Cameroon. The temperature data contained the monthly collected temperatures from the ten meteorological stations in the ten regions during varying yearly collection periods and the sum of the monthly data was used to obtain the yearly mean, minimum and maximum temperature for each station which can be visualized in Table 1.

Stations	Regions	Time period	Mean temperature	Minimum temperature	Maximum temperature
Bafoussam	West	1991-2007	14.4	12.4	16.7
Douala	Littoral	1941-2007	23.1	22.5	24.2
Ebolowa	South	1975-2007	20.4	19.2	22.1
Bamenda	North West	1971-2007	15.3	14.2	15.9
Bertoua	East	1941-2007	18.5	17.3	20.1
Garoua	North	1941-2007	21.7	19.3	23.1
Maroua-Salak	Extreme North	1941-2007	21.6	15.0	25.4
Ngaoundere	Adamawa	1975-2007	15.2	13.6	17.9
Yaoundé	Centre	1943-2007	19.4	18.3	20.6
Ekona	South West	1984-2007	19.3	18.7	19.8

Table 1: Collection stations with mean, minimum and maximum temperatures in Cameroon

3.2.3 Rainfall data

Monthly rainfall data for the Republic of Cameroon were also collected from the Department of Transport, branch of the National Institute of Cartography in Yaoundé. Mean monthly rainfall in Cameroon were collected in millimeters and 1/10 unit measurements for the ten regions of Cameroon. The rainfall data contained the monthly collected rainfall from the 11 meteorological stations in the ten regions during varying yearly collection periods and the sum of the monthly data was used to obtain the yearly mean, minimum and maximum rainfall for each station as seen in Table 2.

Stations	Regions	Time period	Mean rainfall	Minimum rainfall	maximum rainfall
Bafoussam	West	1934-2007	1784.0	1313.7	2366.2
Bamenda	North West	1908-2007	2383.3	78.9	3510.0
Bertoua	East	1939-2007	1512.5	904.2	2039.9
Douala	Littoral	1951-2007	3897.3	2595.9	5327.6
Ebolowa	South	1900-2007	1628.7	0.0	2605.8
Ekona	South West	1965-2003	2059.4	1291.4	2912.2
Garoua	North	1951-2007	1399.4	649.5	2475.5
Maroua	Extreme North	1953-2007	780.7	0.0	1193.8
Ngaoundere	Adamawa	1926-2007	1314.6	0.0	2058.0
Tiko	South West	1958-2007	2446.9	524.2	4078.7
Yaoundé	Centre	1951-2007	1591.5	1143.1	2142.1

Table 2: Collection stations with mean, minimum and maximum rainfall in Cameroon

Tables 1 and 2 shows a numerical representation of the mean, minimum and maximum temperature and rainfall monthly datasets collected from the 10 temperature and 11 rainfall meteorological stations in Cameroon. A graphical visualization of the collected temperature and rainfall stations of the ten regions of Cameroon can be visualized in Figure 5 using the station coordinates.

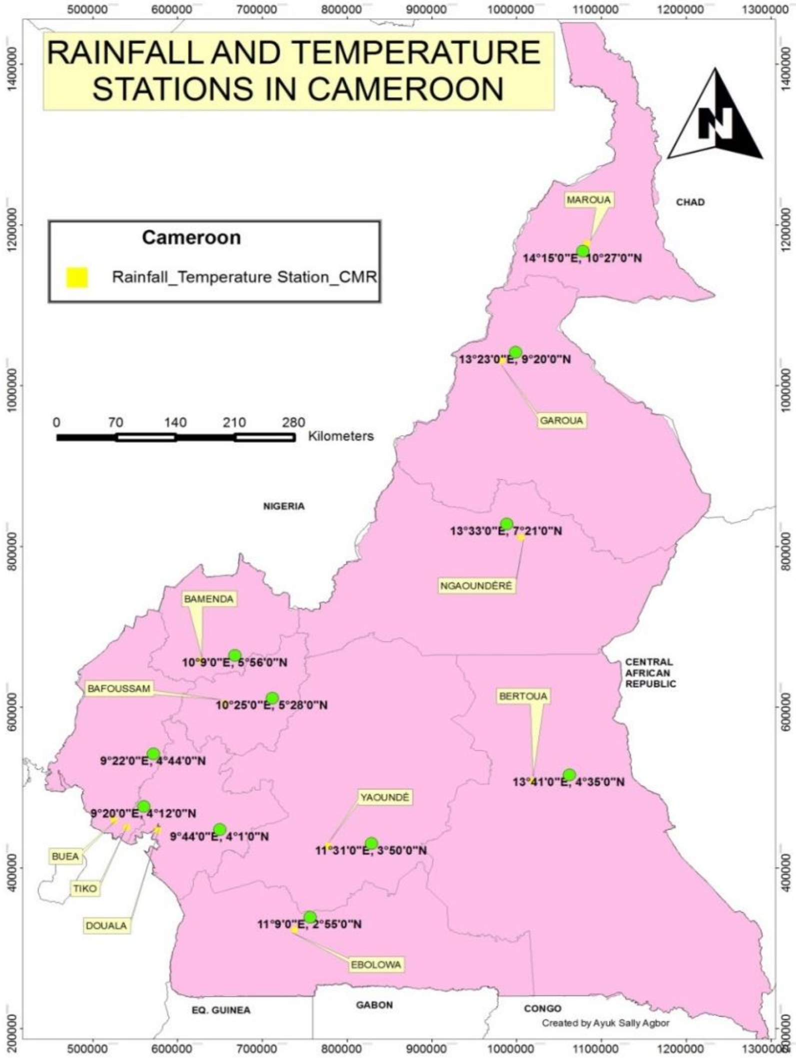


Figure 5: Meteorological stations of Temperature and Rainfall
Source: Author

3.2.4 Water reservoir data

Proximity to water sources especially when polluted is one of the transmitters in enhancing Cholera epidemic. Water reservoir data was collected from digitized water lines in other to identify and calculate the proximity distance from the lakes, rivers and streams to human settlement. The ten main cities within the ten regions were used as centroids.

3.3 Data Preparation

Cholera datasets were collected from 1971 to June 2013 from the Ministry of health in Cameroon. During data pre-processing, missing data was dealt with by using only years which lacked less than ten percent of it missing Cholera data. The collection of location points of Cholera per district were matched with data from the Global Gazatter version 2.2 (http://www.fallingrain.com/world/CM/07/) to get their exact locations in Cameroon using their latitude and longitude coordinate systems. The coordinates were changed to a UTM projection of WGS_84_UTM_zone_32N and a datum of D_WGS_1984 to map their location in ArcMap 10.1 as seen in Figure 4. The monthly rainfall and temperature data collected from the meteorological stations in Cameroon were used in calculating the average, minimum and maximum yearly temperatures and rainfall occurrences including mean rainfall and temperatures during the rainy and dry seasons and the locations of these meteorological stations in Cameroon was map using their latitudes and longitudes coordinates (Figure 5).

3.4 Software

The following software was used for this study:

1. ArcGIS (ArcMap 10.1) for mapping (choropleth maps) and geovisualization, Inverse Distance Weighting (IDW) and geospatial analysis.
2. OpenGeoDa, Version 1.4.6 for Autocorrelation analysis (Local Anselin Moran I or LISA).
3. R-software, Version 3.0.2 for statistical and Spatial Poisson Regression analysis.
4. Microsoft Excel (2010) chart wizard for time series analysis.

4. METHODOLOGY

4.1 Introduction

The methodological framework used in this study is presented in Figure 6, which includes the mapping and geovisualization of Cholera count cases and deaths as well as spatial interpolation of rainfall and temperature using Inverse Distance Weighting (IDW). Time series analysis of Cholera count cases and deaths was done to determine their trends. Spatial analysis was also carried out using local Moran I statistics to evaluate the level of autocorrelation in 2004, 2010, 2011 and 2012 to June 2013. The methodology of interest is:

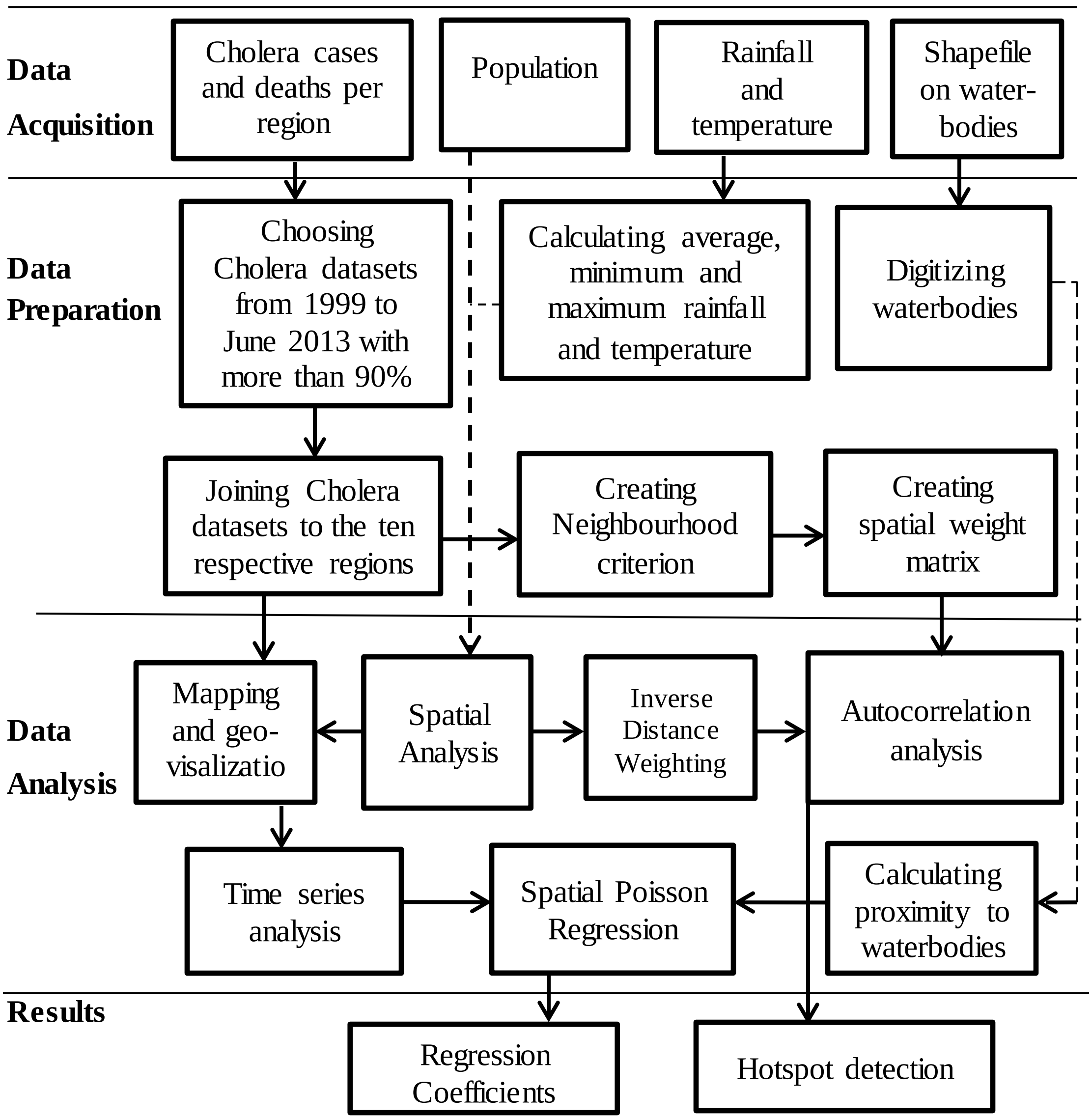


Figure 6: Flow diagram of research methodology

4.2 Data Integration and Visualization

4.2.1 Mapping and geovisualization

Choropleth map: Choropleth maps (thematic map) were used to show population distribution, shaded or patterned areas in proportion to the count Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013 for the ten regions of the Republic of Cameroon. These maps were generated with ArcMap 10.1 and they portrayed the visual weight of the values related to the population, count Cholera cases and deaths as the colour progresses from a low magnitude to a high magnitude representation.

4.3 Temporal Analysis

Time series analysis (plots): Time series analysis was performed using excel chart wizard on the observed Cholera cases and deaths to provide compact description of the data and to visualize the patterns of Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013.

4.4 Spatial Analysis

4.4.1 Inverse Distance Weighting (IDW)

Inverse Distance Weighting (IDW) is a type of deterministic method for multivariate interpolation with a known scattered set of points which is conducted to assigned values to unknown points calculated with a weighted average of the values available at the known points. IDW is a quick deterministic interpolator that requires very few decisions regarding model parameters, because it accounts for distance relationships only. This method assigns weights in an averaging function based on the inverse of the distance to every data points located within a given search radius centered on the point of estimate. IDW interpolation was being performed on the rainfall and temperature data, which was collected from the 11 rainfall and the 10 temperature meteorological stations in Cameroon to get prediction maps.

4.4.2 Proximity analysis

Inhabitants living close to waterbodies are regarded as persons closest to potential Cholera reservoir than those farther. Kummu et al. (2011) concluded that over 50% of the world's population lives closer than 3 km to a surface freshwater body, and only 10% of the population lives further than 10 km away. Hence, in determining the proximity distance from the ten main centroids to the nearest waterbodies (streams and rivers) in Cameroon, shapefiles where obtained from the World Resource Institute (http://www.wri.org/our-work/project/congo-basin-forest-atlases) as seen in Figure 3 and digitized. In this study from the Analysis Tools Extension, the near tool from the Proximity Toolbox was used to determine the distances using a search ratio of 2.5 kilometers and the ten main cities within the ten regions of Cameroon was used as a centroid to the nearest digitized waterbodies using ArcMap 10.1. This process adds three new fields; NEAR_FID which is the ID of each centroid to the closest waterbody, NEAR_DIST is the actual distance using the 2.5 kilometer search ratio from the centroid to the closest waterbody, (-1) indicates that no distance was gotten using a 2.5 kilometer search ratio and NEAR_FC representing the name of the closest waterbody as seen in Table 3

Main cities (centroids)	Regions	NEAR_FID	NEAR_DIST	NEAR_FC
Buea	South West	23457	174	CMR_waterbodies
Bertoua	East	19734	743	CMR_waterbodies
Ebolowa	South	35549	1278	CMR_waterbodies
Bamenda	North West	7533	1619	CMR_waterbodies
Bafoussam	West	11961	1995	CMR_waterbodies
Douala	Littoral	140	1980	CMR_waterbodies
Yaoundé	Centre	26979	1965	CMR_waterbodies
Ngaoundere	Adamawa	-1	-1	/
Garoua	North	201	573	CMR_waterbodies
Maroua	Extreme North	-1	-1	/

Table 3: Proximity of the ten main cities (centroids) to water reservoirs in Cameroon

From Table 3, it can be seen that Buea, Bertoua and Garoua are closest to waterbodies while Ngaoundere and Maroua are farthest as no distance can be determines when a search ratio of 2.5 kilometers was used.

4.5 Autocorrelation Analysis

4.5.1 Local (Anselin) Moran I statistic

Spatial autocorrelation is a measure of the degree to which a set of spatial features and their associated data values tend to be clustered together in space (positive spatial autocorrelation) or dispersed (negative spatial autocorrelation) (GIS Dictionary). Local Moran's I is a local spatial autocorrelation statistic based on the Moran's I statistic and was developed by Anselin (1995) as a local indicator of spatial association or LISA statistic. The Local (Anselin) Moran I statistic which uses the randomization distribution to test null hypothesis of no local autocorrelation (Ho) was conducted on the Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013 for each of the ten regions of Cameroon using GeoDa^{TM}. The statistic is used to calculate each areal unit in the Cholera data and for each polygon within the ten regions of Cameroon.

The index is calculated based on neighbouring polygons with which it shares a border, given a set of weighted features. The Cluster and Outlier Analysis tool identifies spatial clusters of features with attribute values similar in magnitude. A positive value for I*i* (Local Moran) indicates that a region has neighbouring features with similarly high or low attribute values; this region is part of a cluster indicating the HH (High-High) and LL (Low-Low). A negative value for I*i* indicates that a region has neighbouring regions with dissimilar values, thus indicating HL (High-Low) and the LH (Low-High) values with the HL and LH values identified as spatial outliers given a set of weighted Cholera cases/deaths in Cameroon. The Local (Anselin) Moran I statistic for spatial autocorrelation is given as;

$$I_i = z_i \sum_j w_{ij} z_j$$

Where the observations z_i , z_j are in deviations from the mean, and the summation over j is such that only neighbouring values $j \in J_i$ are included and the sum of Local Moran is;

$$\sum_i I_i = \sum_i z_i \sum_j w_{ij} z_j \quad \text{(Anselin, 2010)}$$

The steps in determining the extent of spatial autocorrelation among neighbouring regions are:

1. Choosing a neighbourhood criterion

2. Assigning spatial weights matrix to each region

3. Running statistical test, using weights matrix in order to examine spatial autocorrelation

Choosing a neighbourhood criterion

The first step in analyzing spatial autocorrelation for Cholera cases, deaths and prevalence (cases/population) is to import a shapefile into GeoDa, the next step is to define a neighbourhood criterion over the entire region of Cameroon and the first order Queen's contiguity was used in this study to describes the neighbourhood for the Cholera cases, deaths and prevalence (cases/population) for 2004, 2010, 2011 and 2012 to June 2013.

Generating spatial weights matrix

A spatial weight matrix was created that contains information of the neighbourhood structure for the whole of Cameroon, assigning weights based on shared neighbours as contiguity-based weights are weights based on shared borders and vertices instead of distance.

Running statistical test

GeoDa free software was used to run the Univariate Local Moran I statistic (LISA), by clicking on the Univariate Local Moran I button on the Space toolbar, which popped up a dialog box to insert the generated weights followed by another dialog box with three output options to generate the Cluster Map and the Significant test against the null hypothesis of no spatial autocorrelation was tested to produce a significance Map together with the Moran Scatterplot.

4.6 Spatial Poisson Regression analysis

This study shows the Poisson Regression analysis which seeks to model counts of the total count Cholera cases and deaths used in 2004, 2010, 2011 and 2012 to June 2013. Poisson Regression analysis is used in this study to integrate the response variables used which is the total Cholera count cases (Chocases) and deaths (Chodeaths) for the ten regions of Cameroon and the covariates which are the Average temperature (AvTemp), Average rainfall (AvRain), Distance to the nearest stream in kilometers (DistStmKm), Population (Pop), Latitude (Lat) and Longitude (Long). All count variables have the same length of observational time (for the ten regions of Cameroon) and the model will not need any adjustment to account for varying lengths of observational time.

5. RESULTS AND ANALYSIS

5.1 Mapping and geovisualization (Choropleth mapping)

The choropleth maps generated shows population distribution in Cameroon from 2010 to June 2013 and the count Cholera cases and deaths in 2004, 2010, 2011 and 2012 to June 2013 within the ten regions of Cameroon. Each of the region is been colored accordingly as it directly represents the magnitude of the population, count Cholera cases and deaths. The highest counts/rates are represented with a Mars Red colour while the lowest counts/rates are represented with a leaf Green colour as seen from each of the legends (Figures 7, 8 and 9). These maps highlight two extremes in the population distribution, Cholera count cases and deaths in Cameroon.

5.1.1 Population distribution in Cameroon

The Republic of Cameroon has conducted three successful censuses. The first census was conducted on the 9th of April 1976 resulting in a total of 7131833 count numbers, the second census gave a total of 10493655 count numbers on the 10th of April 1987 and the third census was conducted on the 1st of November 2005 with a total of 17463836 count numbers (GeoHive, National Institute of Statistics, Cameroon). Nevertheless, the population of Cameroon has continued to be counted since 2005 for each of the ten regions. The population of Cameroon in 2010 was 19406100 inhabitants (GeoHive, National Institute of Statistics, Cameroon), in 2011 the population increased to 19633041 inhabitants, in 2012 the population was 20607603 inhabitants and up to June of 2013, the population of Cameroon has increased to 20883039 inhabitants (Ministry of Public health, Yaoundé, Cameroon).

The choropleth maps (Figure 7) below shows the population distribution for each of the ten regions of Cameroon from 2010 to June 2013. Five colours have been used to distinguish the count population numbers as represented in each region. The maps show the highest population counts in the Littoral, Extreme North and Centre regions from 2010 to June 2013 with an increase in population in the North region of Cameroon from 2012 to June 2013 as this region has a refugee camp. Population increase is also evident in the Adamawa, North West, South West and West regions while the South and East regions have grown in an almost constant rate.

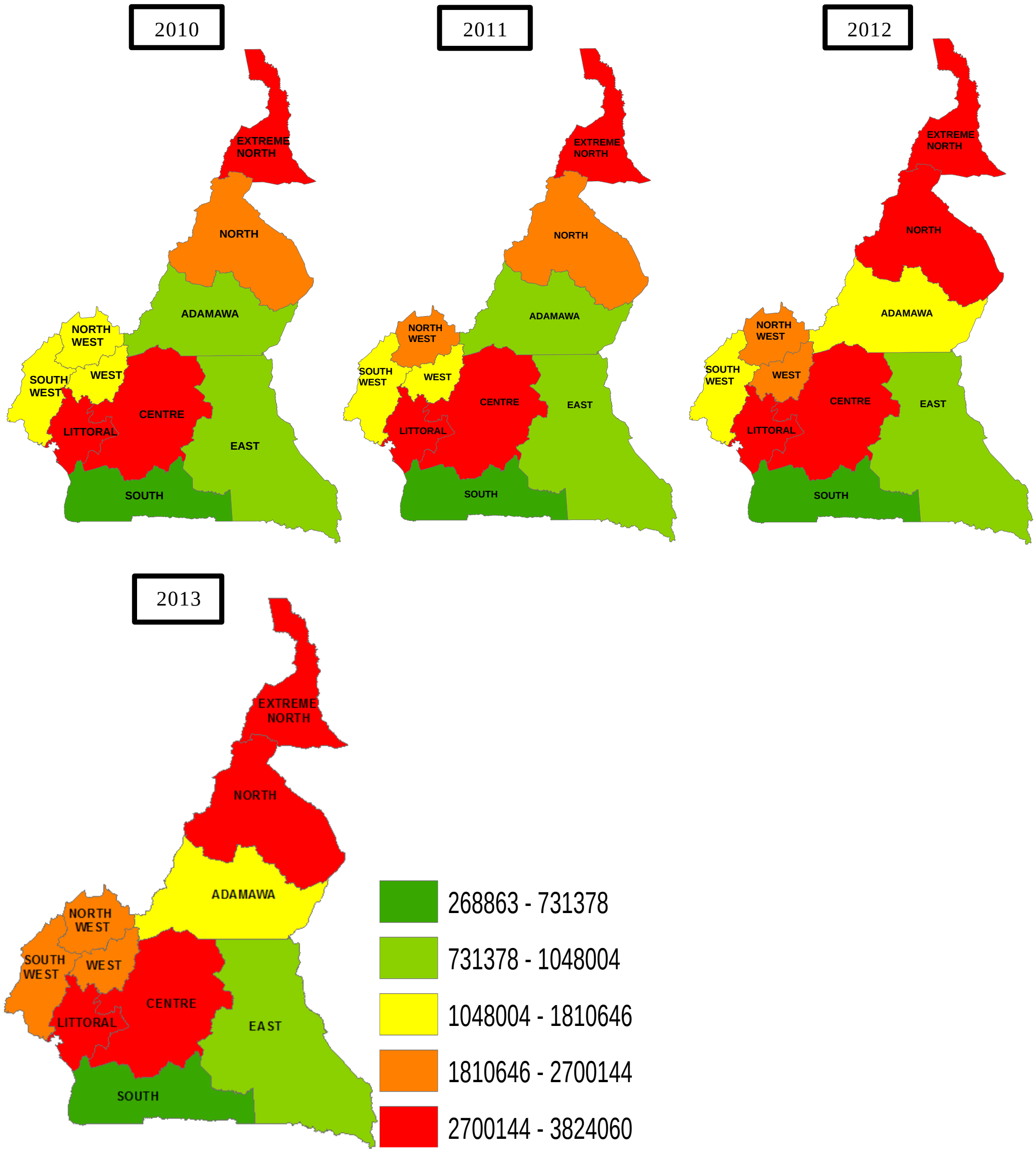


Figure 7: Population distribution in Cameroon from 2010 to June 2013

5.1.2 Count Cholera cases in Cameroon

For the spatial analysis of the Cholera epidemic in Cameroon, choropleth maps (Figure 8) were used to show the Cholera count cases in 2004, 2010, 2011 and 2012 to June 2013. Patterns visualizing the highest Cholera count cases can be observed in the Extreme North (2010 and 2011), North (2011) and Littoral regions (2004 and 2011), mean Cholera cases can be seen in the West (2004 and 2011), South West (2011) and Centre (2011) regions while the lowest counts occur in the Extreme

North (2012 to June 2013), North (2004, 2010,and 2012 to June 2013), Adamawa (2004, 2010, 2011, 2012 to June 2013), North West (2004, 2010,2011, 2012 to June 2013), South West (2004, 2010,and 2012 to June 2013), West (2010 and 2012 to June 2013), Littoral (2010 and 2012 to June 2013), Centre (2004, 2010,and 2012 to June 2013), East (2004, 2010, 2011, 2012 to June 2013) and South (2004, 2010, 2011, 2012 to June 2013).

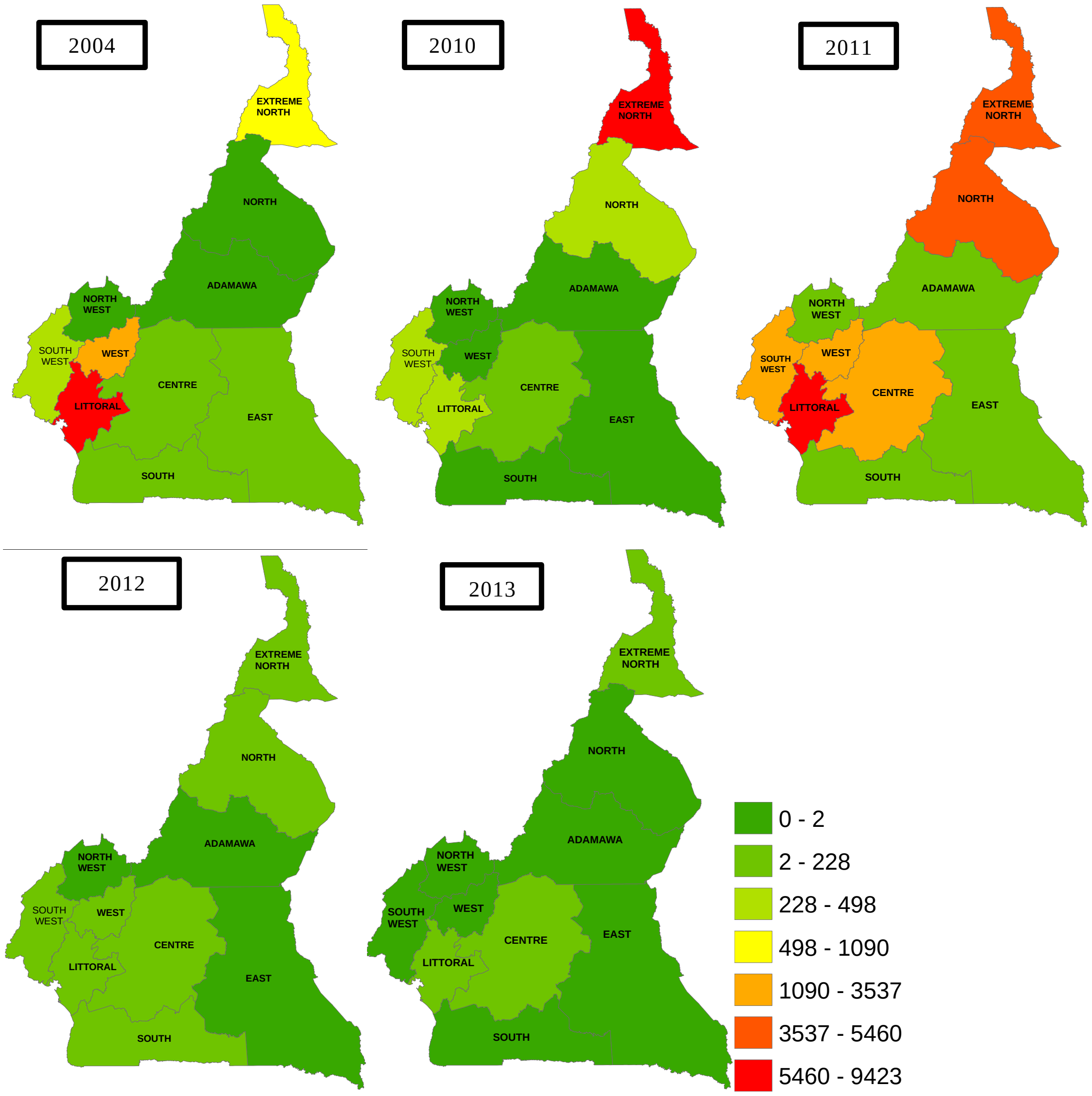


Figure 8: Count Cholera cases in 2004, 2010, 2011 and 2012 to June 2013 in Cameroon

5.1.3 Count Cholera Deaths in Cameroon

For the spatial analysis of Cholera epidemic in a Cameroon, choropleth maps (Figure 9) of count Cholera Deaths in 2004, 2010, 2011 and 2012 to June 2013 was done to visually geomap the spatial distribution within the ten regions of Cameroon. The highest Count Cholera deaths in Cameroon can be seen in the Extreme North (2010 and 2011) and North (2011) regions, mean deaths in the Littoral (2011) and Centre (2011) regions, the lowest count Cholera deaths occur in the Extreme North (2004 and 2012 to June 2013), North (2004, 2010 and 2012 to June 2013), Adamawa (2004, 2010, 2011 and 2012 to June 2013), North West (2004, 2010, 2011 and 2012 to June 2013), South West (2004, 2010, 2011 and 2012 to June 2013), West (2004, 2010, 2011 and 2012 to June 2013), Littoral (2004, 2010 and 2012 to June 2013), Centre (2004, 2010, 2012 to June 2013), East (2004, 2010, 2011 and 2012 to June 2013) and South (2004, 2010, 2011 and 2012 to June 2013).

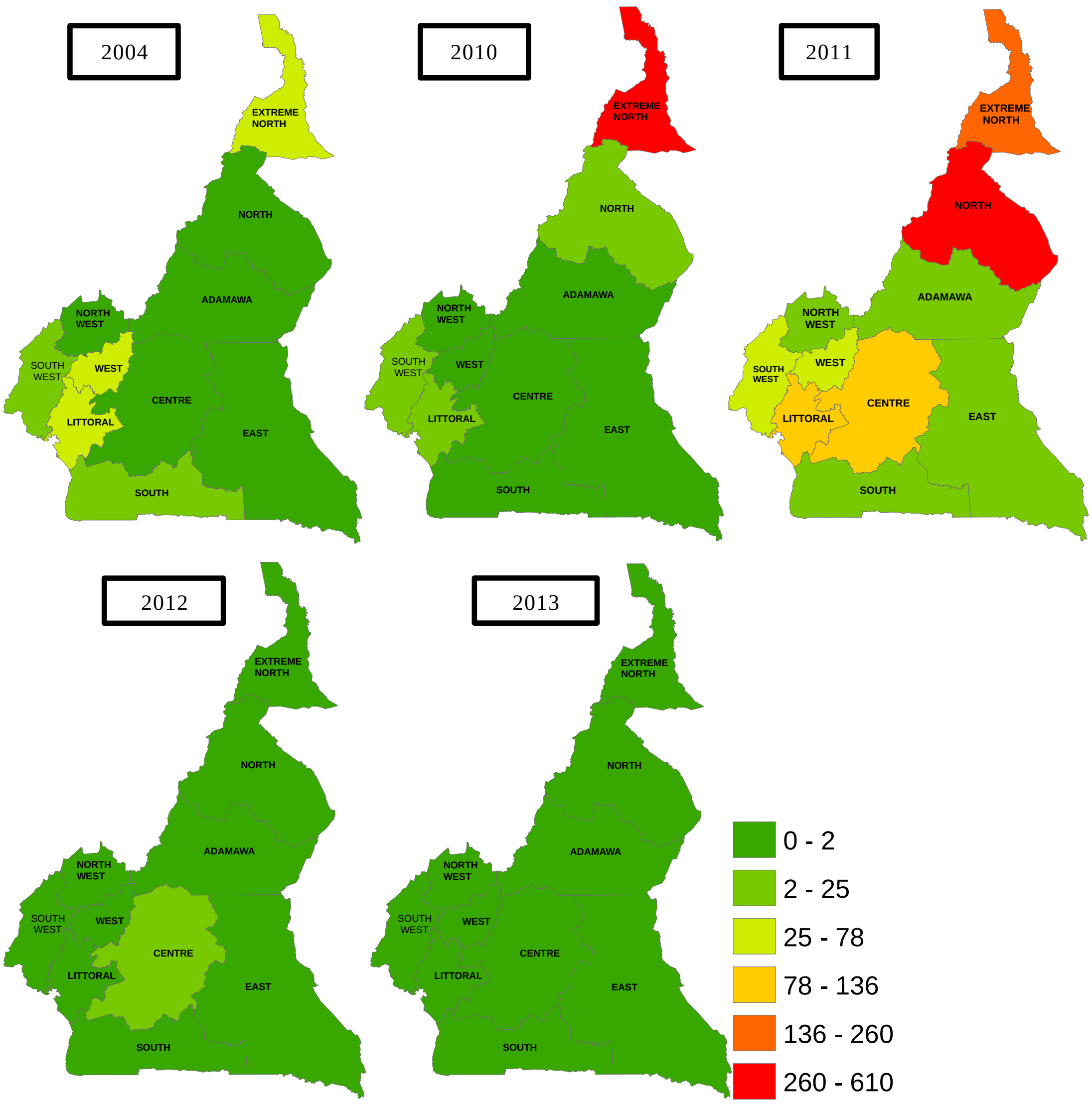


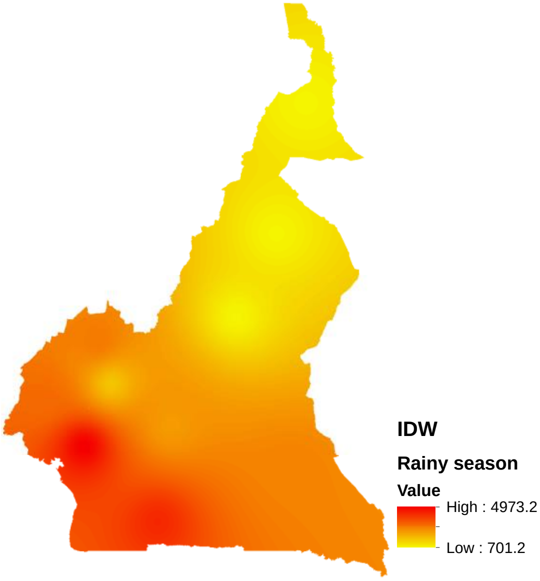
Figure 9: Count Cholera deaths in 2004, 2010, 2011 and 2012 to June 2013 in Cameroon

5.2 Inverse Distance Weighting (IDW)

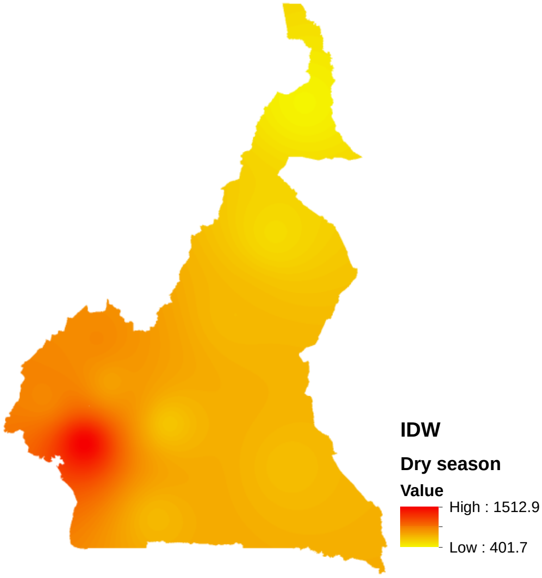
IDW was used to create prediction maps of climatic data (rainfall and temperature) gotten from the 11 rainfall and the 10 temperature meteorological stations within the ten regions of Cameroon based on the two seasons (rainy and dry seasons) in order to get the rainfall and temperature extremes. The values of the rainfall and temperature data are represented as interpolated surfaces.

5.2.1 Interpolated rainfall surface during the rainy and dry season in Cameroon

Figure 10a shows an interpolated IDW surface of rainfall measured in millimeters during the rainy season with an average low count of 701.2 millimeters and an average high count of 4973.2 millimeters, which visualizes high rainfall in the North West, South West, Littoral and South, mean rainfall in the East region and low rainfall in the West, Adamawa, North, Centre and Extreme North regions. Figure 10b shows an interpolated IDW surface of rainfall measured in millimeters during the dry season with an average low count of 401.7 millimeters and an average high count of 1512.9 millimeters, which visualizes high rainfall only in the Littoral region, mean rainfall in the South West, West and North West regions and low rainfall can be seen in the Extreme North, North, Adamawa, Centre, East and South regions.



(a) Rain during the rainy season

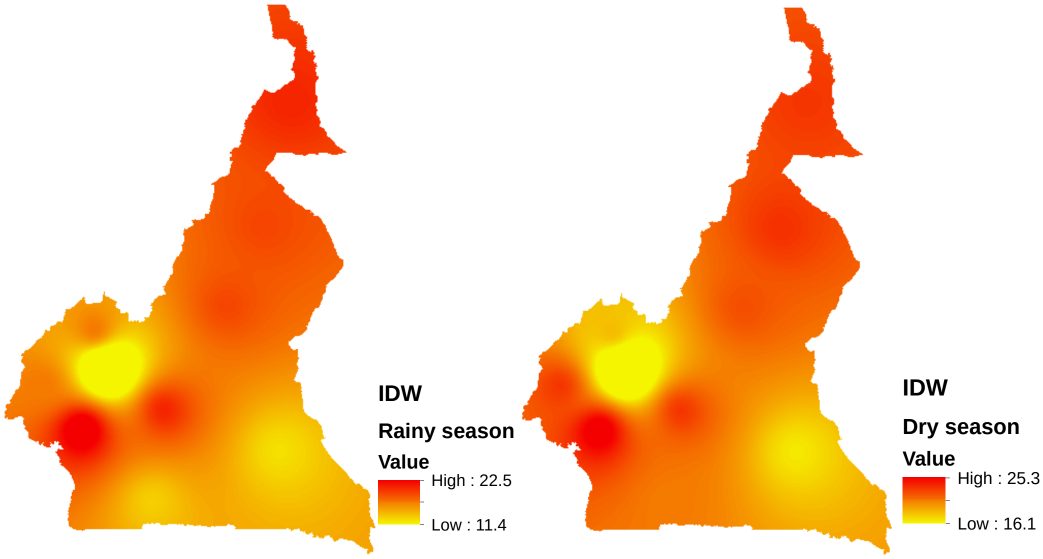


(b) Rain during the dry season

Figure 10: IDW Interpolated rainfall surface during the rainy and dry season in Cameroon

5.2.2 Interpolated temperature surface during the rainy and dry season in Cameroon

Figure 11a shows an interpolated IDW surface of temperature measured in Celsius during the rainy season with an average low temperature of 11.4 Celsius and an average high temperature of 22.5 Celsius which visualizes the highest temperatures in the Extreme North, North, Adamawa, Centre and Littoral regions and low temperatures in the North West, South West, West, East and South regions. Figure 11b illustrates an interpolated IDW surface of temperature during the dry season with an average low temperature of 16.1 Celsius and an average high temperature of 25.3 Celsius. The highest temperatures are in the Extreme North, North, Adamawa, Centre, Littoral and South West regions with the lowest in the North West, West, and East regions. Therefore patterns of high temperatures are observed in the Extreme North, North, Littoral, Centre, South and South West regions with low temperatures in the Adamawa, North West and West regions.

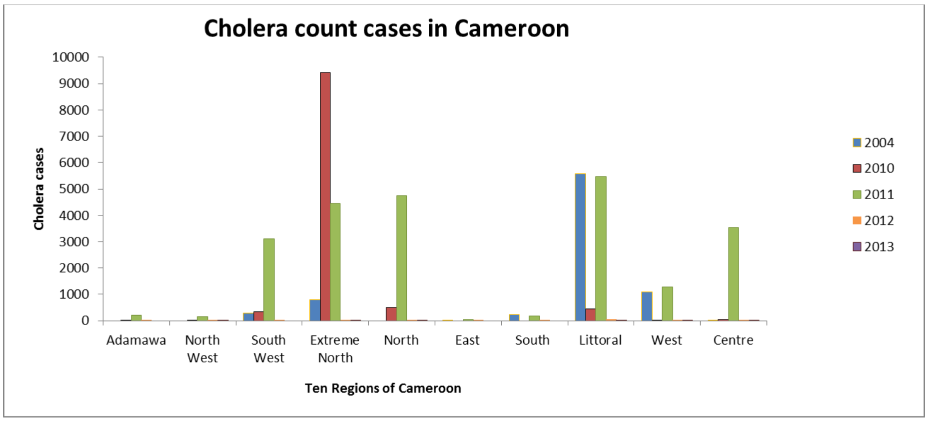


(a) Temperature during the rainy season (b) Temperature during the dry season

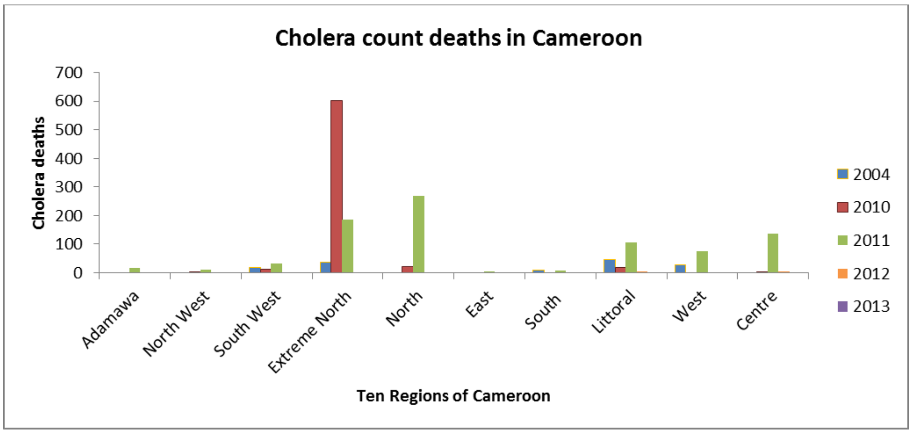
Figure 11: IDW Interpolated temperature surface during the rainy and dry season in Cameroon

5.3 Time series analysis

Time series analysis was conducted with the use of excel chart wizard 2010 for the Cholera count incidence (cases/deaths) in 2004, 2010, 2011 and 2012 to June 2013. The graphs (Figure 12a and b) shows the primary horizontal axis representing the ten regions of Cameroon and the primary vertical axis represents the Cholera count cases/deaths in 2004, 2010, 2011 and 2012 to June 2013. From the charts, patterns of high Cholera count cases and high deaths can be found in the Extreme North (2010 and 2011) and North (2011) regions while patterns of high Cholera count cases and low deaths are visualized in the South West (2011), Littoral (2004 and 2011) and Centre (2011) regions.



(a) Cholera count cases in Cameroon



(b) Cholera count deaths in Cameroon

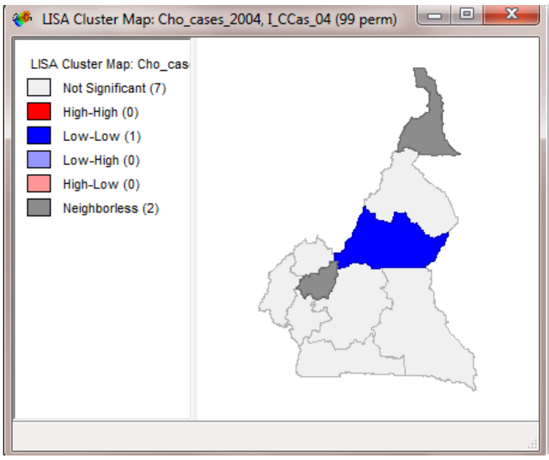
Figure 12: Time series analysis of Cholera cases and deaths in Cameroon

5.4 Local (Anselin) Moran I statistic

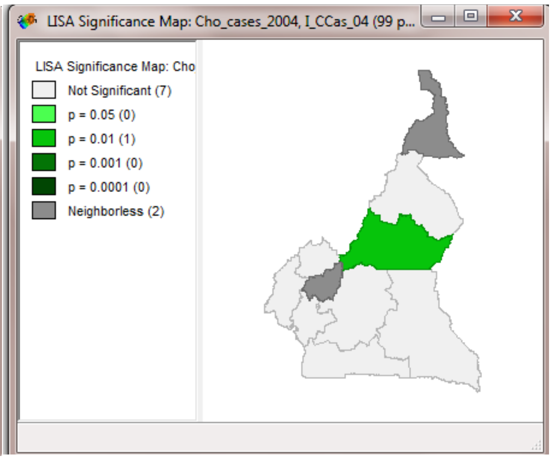
The Univariate LISA Cluster Map indicates six cluster levels, which are; Not Significant, High-High, Low-Low, Low-High, High-Low and Neighbourless. The LISA Significance Map illustrates six levels which are; Not Significant, p = 0.05, p = 0.01, p = 0.001 and p = 0.0001 based on the number of permutations from 99 (1/100=0.01) up to 999 (1/1000=0.001) and Neighbourless. The Local Moran scatterplot gives four types of spatial autocorrelation from the four quadrants indicating the High-High (upper right), Low-High (upper left), Low-Low (lower left) and High-Low (lower right) differentiating the four quadrants.

5.4.1 Local Moran I statistic on count Cholera cases in 2004

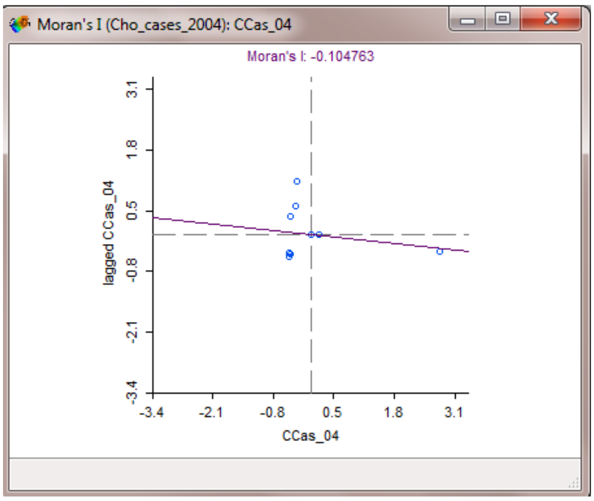
From the Local Moran I Statistic carried out on the count Cholera cases recorded in 2004 (Figure 13), the LISA Cluster map visualizes a Low-Low cluster giving a positive spatial autocorrelation in the Adamawa region meaning there is a low Cholera count case in this region been surrounded by neighbours with low Cholera count cases. The LISA Significance Map shows a level of significance at 0.01 with its neighbours, the Local Moran I scatterplot gives a Moran I of -0.104763 with the lower-left visualizing a Low-Low spatial autocorrelation as seen in the Adamawa region.



(a) LISA cluster map



(b) LISA significance map

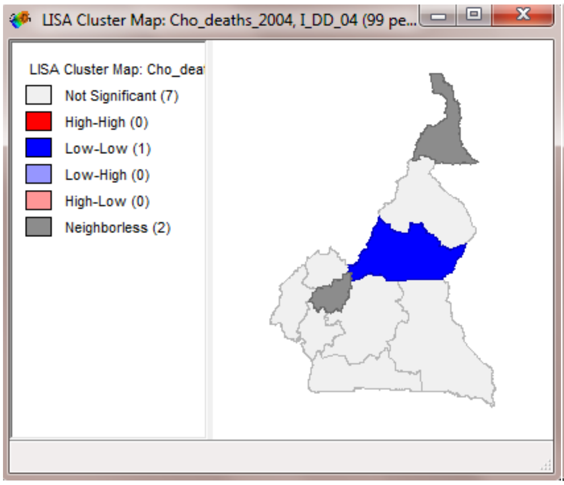


(c) LISA scatterplot

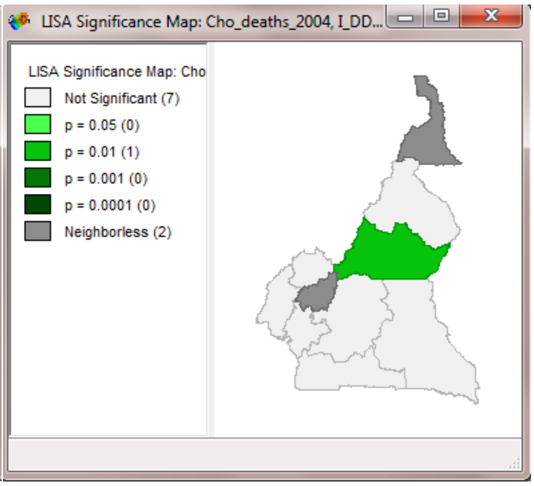
Figure 13: Local Moran I statistic of Cholera cases in 2004 in Cameroon

5.4.2 Local Moran I statistic on count Cholera deaths in 2004

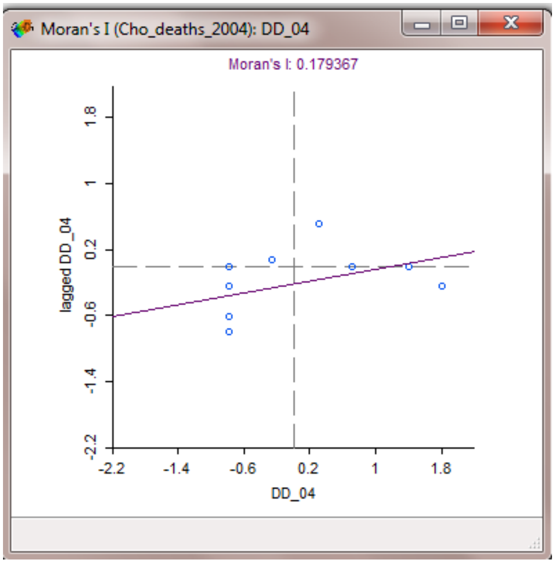
Cholera count deaths in 2004 (Figure 14) also shows a Low-Low cluster in the Adamawa region as low Cholera deaths in the Adamawa region is surrounded by low count deaths by its neighbours (North, North West, Centre and East regions). The LISA Significance Map shows a 0.01 alpha level statistical significance and the Local Moran scatterplot illustrates a strong Low-Low positive spatial autocorrelation visualized in the Adamawa region in the lower-left, a High-High positive autocorrelation from the upper-right and a High-Low negative spatial autocorrelation from the lower- right quadrants with an observed Moran I of 0.179367.



(a) LISA cluster map



(b) LISA significance map

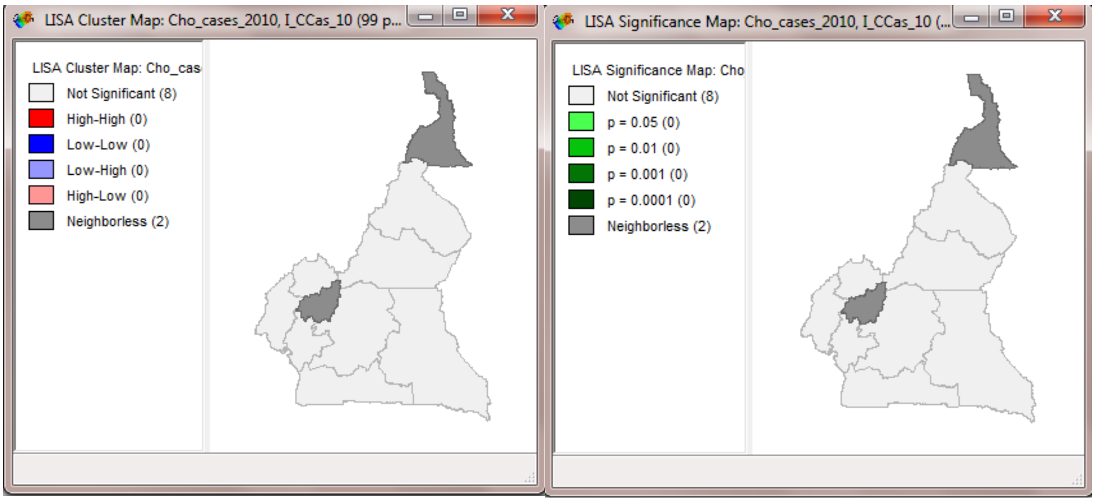


(c) LISA scatterplot

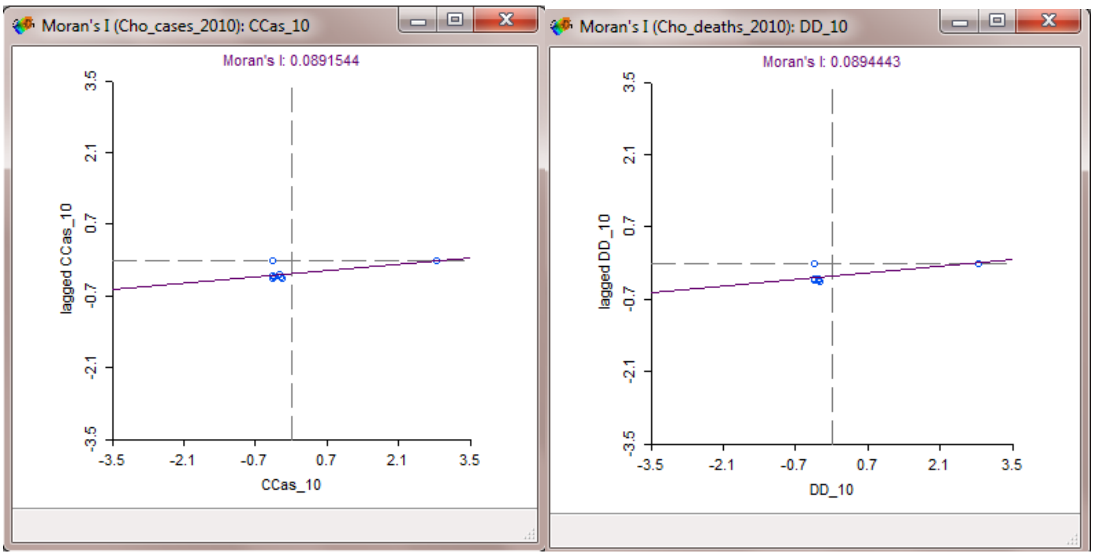
Figure 14: Local Moran I statistic of Cholera deaths in 2004 in Cameroon

5.4.3 Local Moran I statistic on count Cholera cases and deaths in 2010

The Cholera count cases in 2010 (Figure 15a and b) shows a LISA Cluster and Significance Map of Not Significant (Areas that are not significant at a default pseudo significance level of 0.05) spatial autocorrelation in 8 regions. The Local Moran scatterplot of Cholera cases in 2010 (Figure 15c) shows a Low-Low positive relationship giving a Moran I of 0.0891544. The Cholera deaths in 2010 also show a LISA Cluster and Significance Map indicating no spatial autocorrelation (Figure 15a and b). The Local Moran scatterplot (Figure 15d) indicate a Low-Low positive relationship showed by the lower left quadrant and a Moran I of 0.0894443.



(a) LISA cluster map (b) LISA significance map

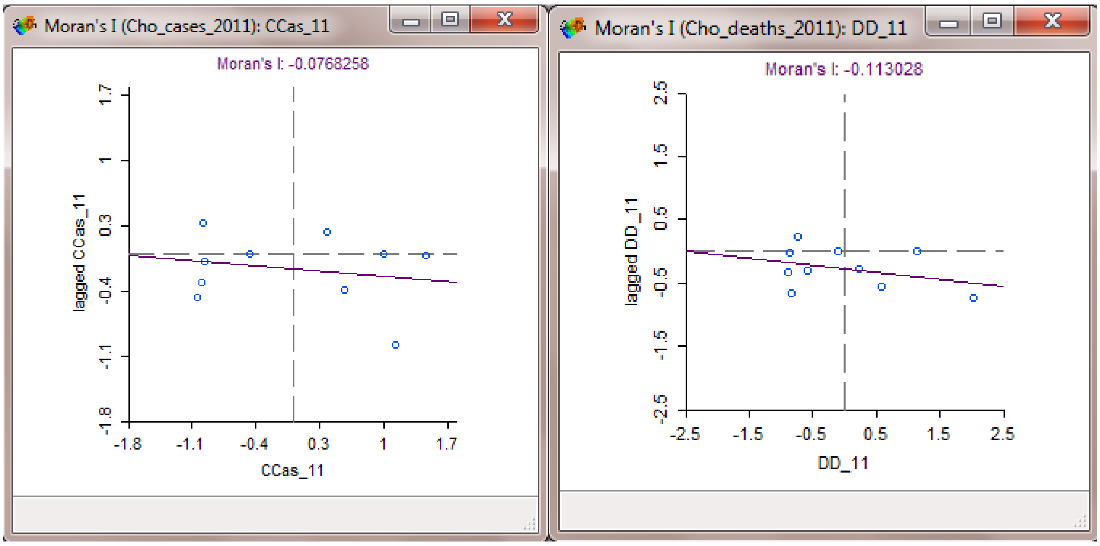


(c) LISA scatterplot for 2010 count cases (d) LISA scatterplot for 2010 count deaths

Figure 15: Local Moran I statistic of Cholera cases and deaths in 2010 in Cameroon

5.4.4 Local Moran I statistic on count Cholera cases and deaths in 2011

In 2011 (Figure 16), the Cholera count cases and deaths shows both a Cluster and Significance Map of Not Significant level of autocorrelation as seen in Figure 15a and b, while the Local Moran scatterplot (Figure 16a), shows relationships in all of the four quadrants as the upper-right shows a High–High positive autocorrelation, the upper-left shows a Low-High negative autocorrelation, the lower-right showing a High-Low negative spatial autocorrelation, a Low-Low positive spatial autocorrelation from the lower left with a Local Moran I of -0.0768258. The Local Moran scatterplot (Figure 16b), indicates three relationships from the four quadrants, the upper-left indicates a Low-High negative spatial autocorrelation, the lower-left indicates a Low-Low positive spatial autocorrelation and the lower- right indicates a High-Low negative spatial autocorrelation with a Local Moran I of -0.113028.

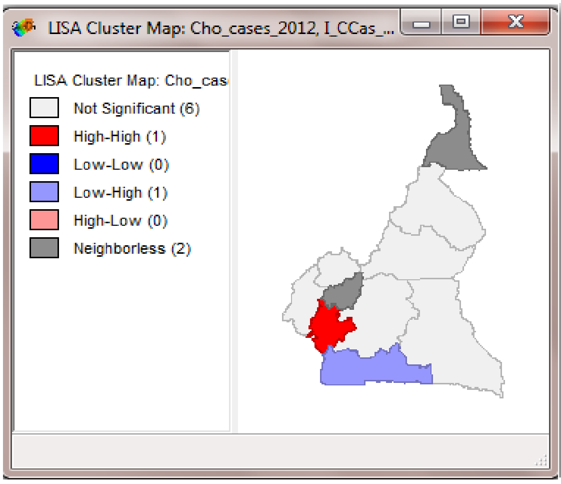


(a) LISA scatterplot for 2011 count cases (b) LISA scatterplot for 2011 count deaths

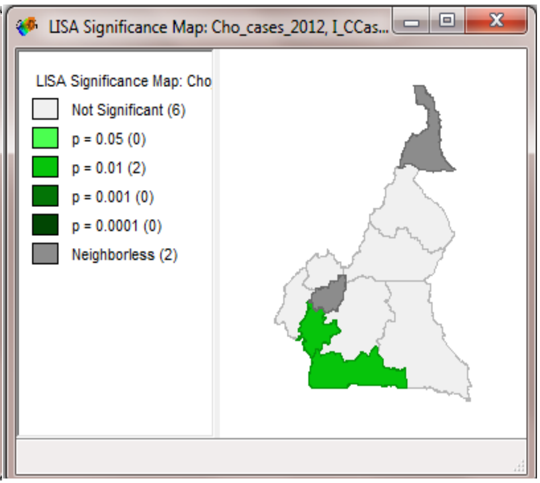
Figure 16: Local Moran I statistic of Cholera cases and deaths in 2011 in Cameroon

5.4.5 Local Moran I statistic on count Cholera cases in 2012

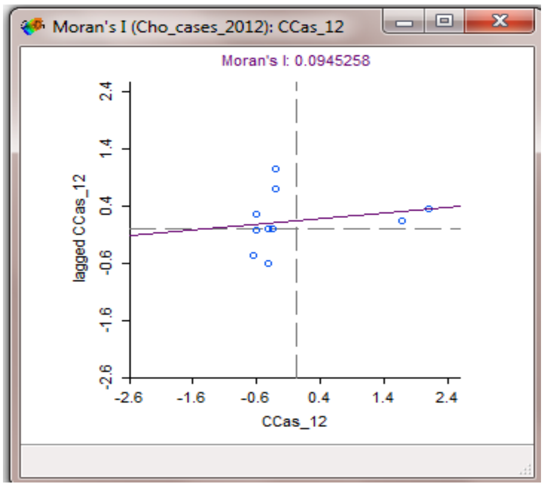
The count Cholera cases in 2012 (Figure 17) shows a LISA Cluster Map with a Low-High cluster in the South region indicating a low outlier among high neighbours giving a negative spatial autocorrelation and a High-High cluster in the Littoral region with a high count Cholera case value in the Littoral region and its neighbours. The LISA Significance Map illustrates a 0.01 alpha level of significance while the Local Moran scatterplot shows a High-High positive spatial autocorrelation as visualized in the Littoral region (upper-right quadrant), a Low-High negative spatial autocorrelation is seen from the upper left quadrant as visualized in the South region and a Low-Low spatial autocorrelation in the lower-left quadrant with a Local Moran I of 0.0945258.



(a) LISA cluster map



(b) LISA significance map

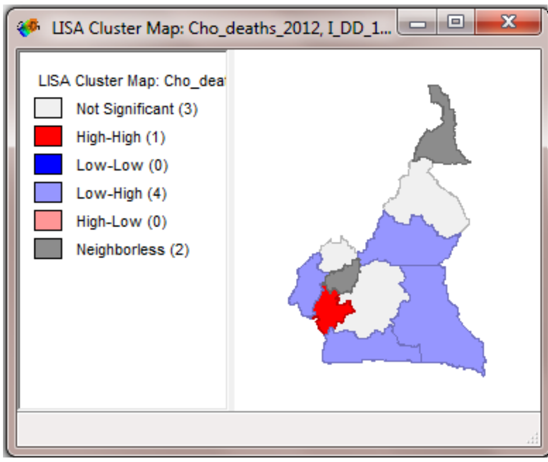


(c) LISA scatterplot

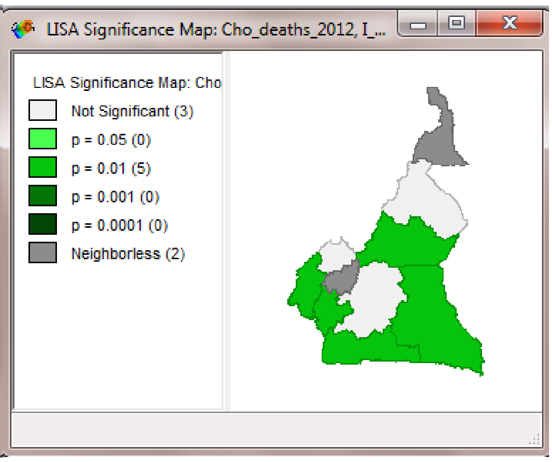
Figure 17: Local Moran I statistic of Cholera cases in 2012 in Cameroon

5.4.6 Local Moran I statistic on count Cholera deaths in 2012

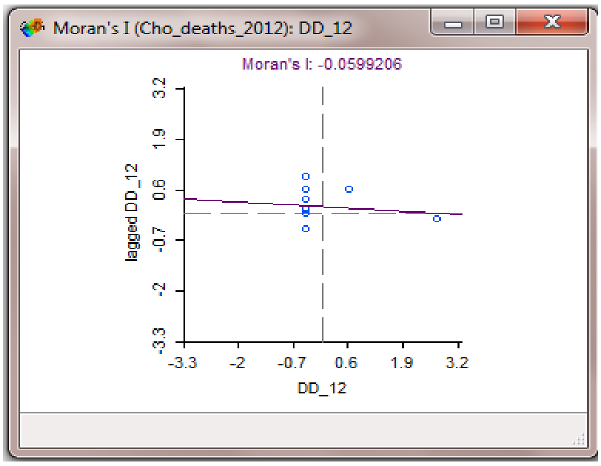
The count Cholera deaths in 2012 (Figure 18) shows a LISA Cluster Map having a Low-High negative autocorrelation in the Adamawa, South West, East and South regions and a High-High positive spatial autocorrelation in the Littoral region. The LISA Significance Map gives a 0.01 alpha level of Significance and the Local Moran I scatterplot illustrates a Low-High negative spatial autocorrelation visualized from the upper left quadrant in the Adamawa region, South West, East and South regions, a High-High (upper-right quadrant) positive spatial autocorrelation as seen in the Littoral region and also a Low-Low (lower-left quadrant) spatial autocorrelation with an observed Local Moran I of -0.0599206.



(a) LISA cluster map



(b) LISA significance map



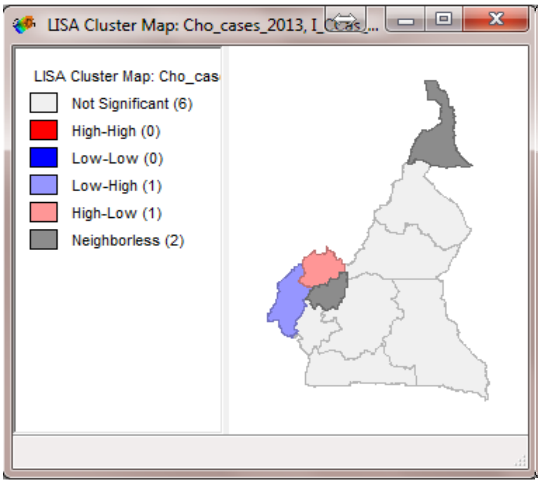
(c) LISA scatterplot

Figure 18: Local Moran I statistic of Cholera deaths in 2012 in Cameroon

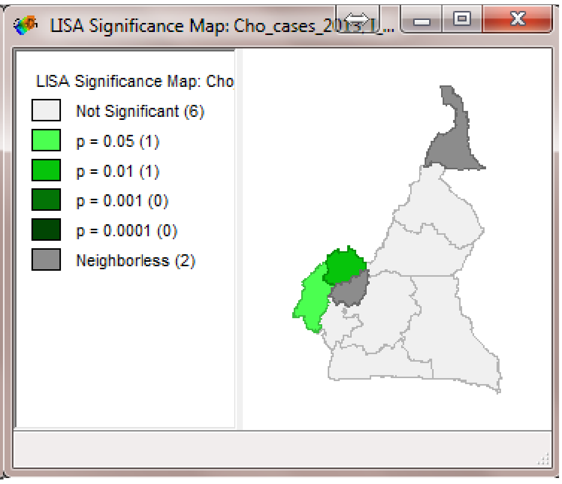
5.4.7 Local Moran I statistic on count Cholera cases in 2013

The Cholera count cases in 2013 (Figure 19) shows a High-Low cluster in the North West region indicating a high outlier among low neighbours giving a negative autocorrelation and a Low-High cluster in the South West region. The LISA Significance Map shows a 0.01 and 0.05 alpha levels of significance in the North West and South West regions respectively. The Local Moran I scatterplot illustrates a Low-High negative autocorrelation (upper-left), as seen in the South West region, a High-Low negative spatial autocorrelation in the lower-right quadrant as seen in the

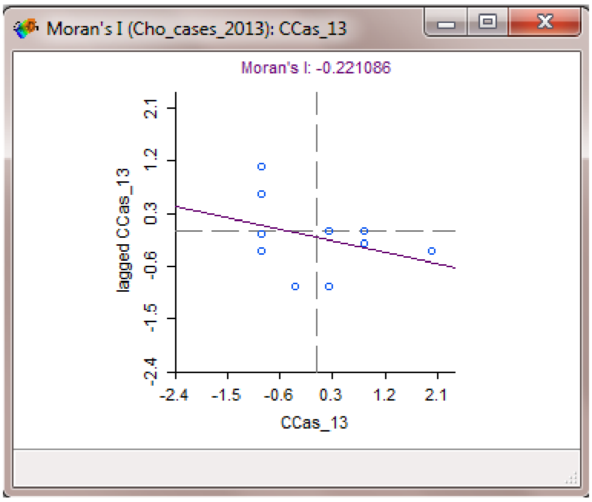
North West region, a Low-Low positive spatial autocorrelation in the lower-left quadrant and an observed Local Moran I of -0.221086.



(a) LISA cluster map



(b) LISA significance map

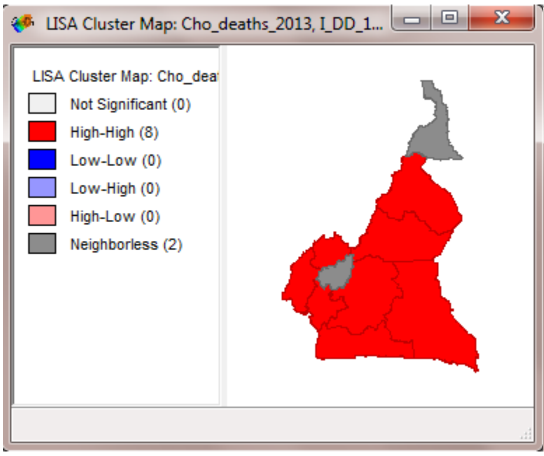


(c) LISA scatterplot

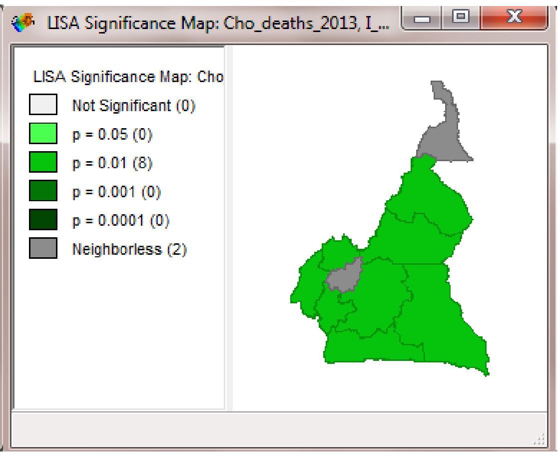
Figure 19: Local Moran I statistic of Cholera cases in 2013 in Cameroon

5.4.8 Local Moran I statistic on count Cholera deaths in 2013

Cholera count deaths in 2013 (Figure 20) shows a High-High spatial autocorrelation in the Adamawa, North, North West, South West, Centre, Littoral, South and East regions indicating that there are high count Cholera deaths in these eight regions surrounded by high death counts in neighbouring regions with the Extreme North and West regions indicating a neighbourless connectivity. The LISA Significance Map indicates a 0.01 alpha level of significance in all of the eight regions and the Local Moran scatterplot gives a Moran I of zero (0).



(a) LISA cluster map



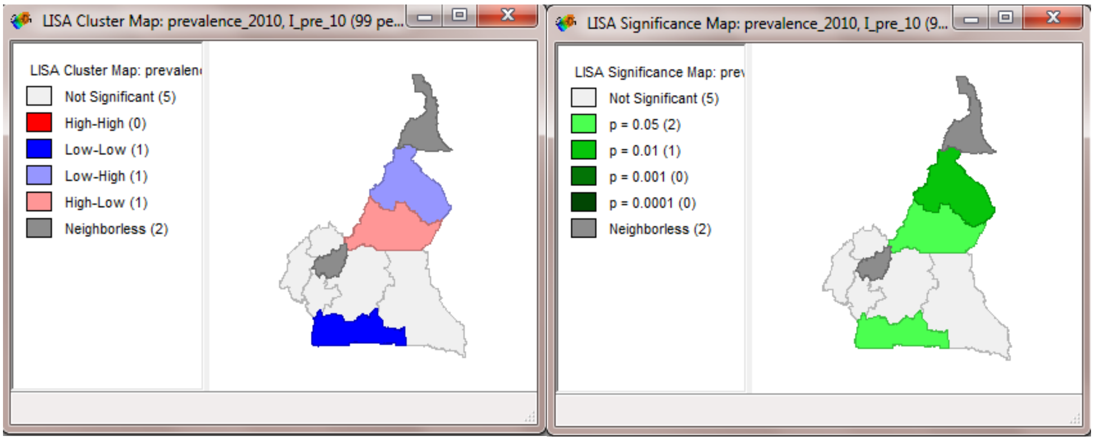
(b) LISA significance map

(c) LISA scatterplot

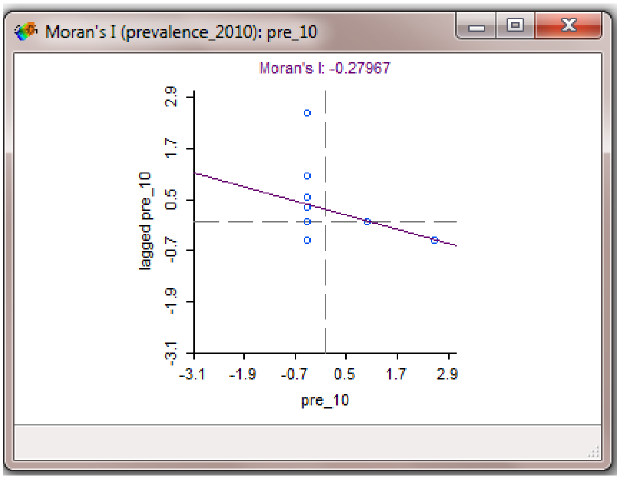
Figure 20: Local Moran I statistic of Cholera deaths in 2013 in Cameroon

5.4.9 Local Moran I statistic of prevalence in 2010

The prevalence (cases/population) in 2010 (Figure 21) gave a LISA Cluster Map of Low-Low positive spatial autocorrelation in the South region, indicating a low prevalence in 2010 among low neighbours, Low-High negative spatial autocorrelation in the North region, indicating a low outlier among high neighbours and a High-Low cluster in the Adamawa region, indicating a high outlier among low neighbours thus a negative autocorrelation. The LISA Significance Map shows a 0.01 (North region) and a 0.05 (South and Adamawa regions) alpha level and the Local Moran scatterplot visualizes a Low-High negative spatial autocorrelation (upper-left quadrant) as seen in the North region, Low-Low positive spatial autocorrelation (lower-left quadrant) as seen in the South region and a High-Low negative spatial autocorrelation (lower-right quadrant) as seen in the Adamawa region with a Moran I of -0.27967.



(a) LISA cluster map (b) LISA significance map

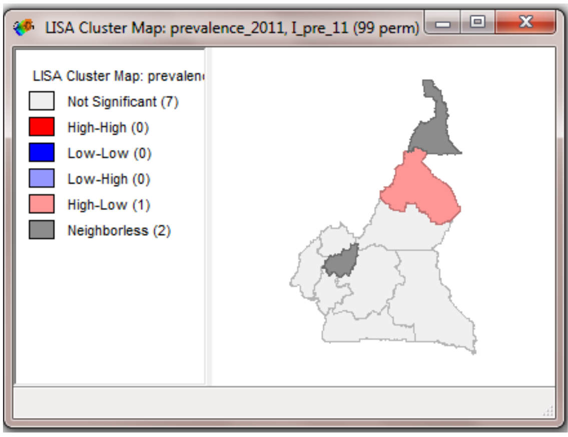


(c) LISA scatterplot

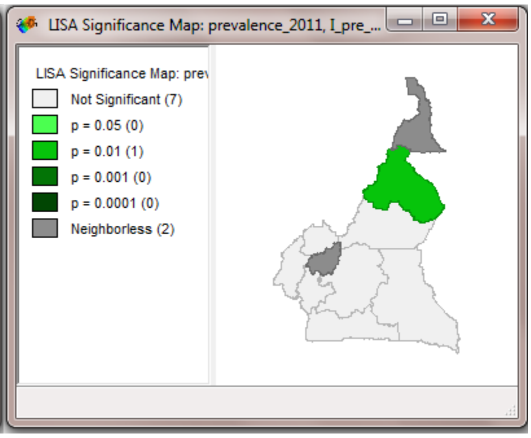
Figure 21: Local Moran I statistic of prevalence in 2010 in Cameroon

5.4.10 Local Moran I statistic of prevalence in 2011

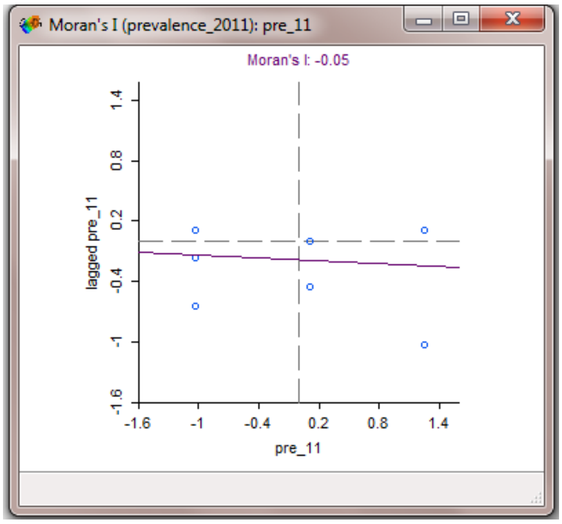
The prevalence of 2011 (Figure 22) gives a LISA Cluster Map of High-Low cluster in the North region, indicating a high outlier surrounded by low neighbours, thus negative spatial autocorrelation. The LISA Significance Map gives a 0.01 level of significance and the Local Moran I scatterplot shows a High-High positive spatial autocorrelation (upper-right), Low-High negative autocorrelation (upper-left), Low-Low positive spatial autocorrelation (lower-left) and a strong High-Low (lower-right) spatial autocorrelation exists in the North region and a Local Moran I of -0.05.



(a) LISA cluster map



(b) LISA significance map

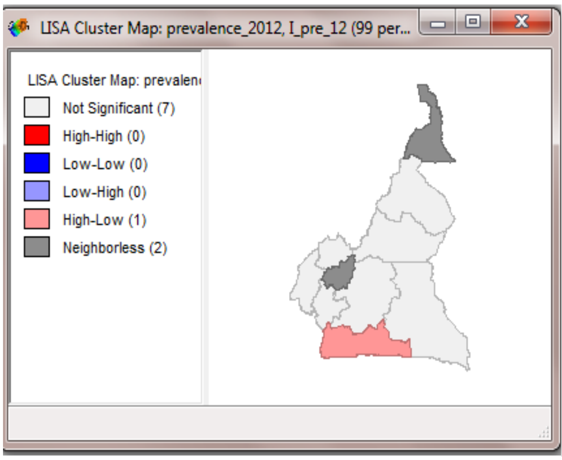


(c) LISA scatterplot

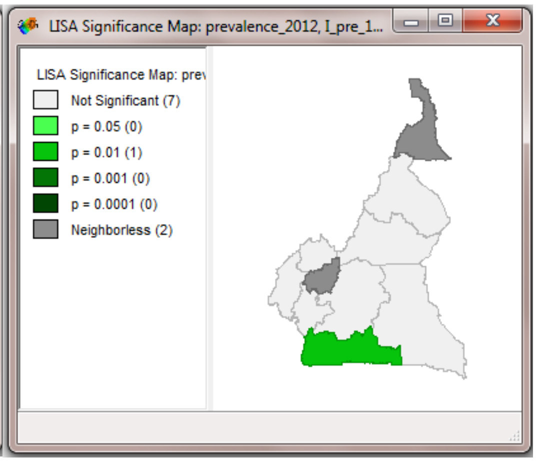
Figure 22: Local Moran I statistic of prevalence in 2011 in Cameroon

5.4.11 Local Moran I statistic of prevalence in 2012

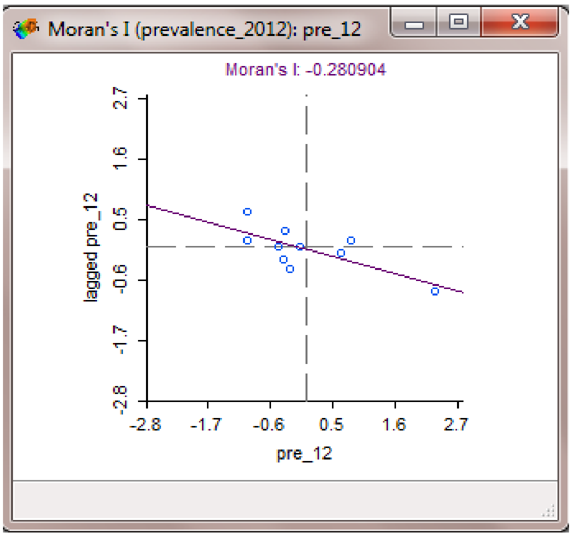
The prevalence of 2012 (Figure 23) graphically visualizes a High-Low negative spatial autocorrelation in the South region, thus a high outlier among low neighbours. The LISA Significance Map gives a 0.01 alpha level of significance and the Local Moran scatterplot illustrates four autocorrelation levels indicating a High-High positive spatial autocorrelation (upper-right), a Low-High negative spatial autocorrelation (upper-left), a Low-Low positive spatial autocorrelation (lower-left) and a High-Low negative spatial autocorrelation (lower-right) as seen in the South region with an observed Local Moran I of -0.280904.



(a) LISA cluster map



(b) LISA significance map

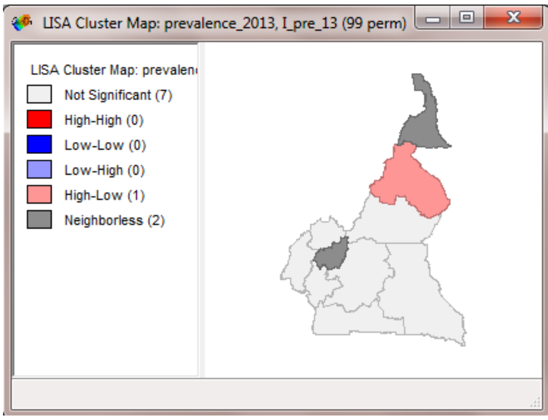


(c) LISA scatterplot

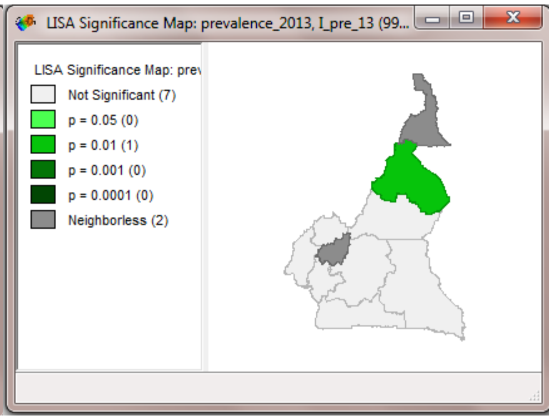
Figure 23: Local Moran I statistic of prevalence in 2012 in Cameroon

5.4.12 Local Moran I statistic of prevalence in 2013

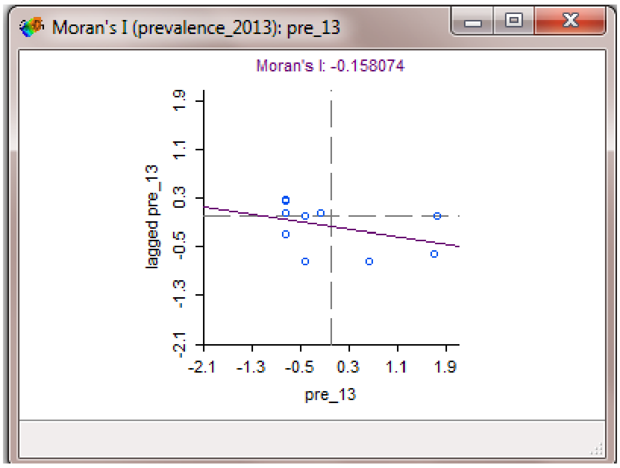
The prevalence of 2013 (Figure 24) graphically shows a High-Low cluster in the North region which indicates a high outlier with low neighbours and the LISA Significance Map shows a p-value of 0.01 alpha level of significance. Local Moran I scatterplot indicates a Low-High negative spatial autocorrelation (upper-left), a Low-Low positive autocorrelation (lower-left) and a High-Low negative spatial autocorrelation (lower-right) as seen in the Adamawa region with an observed Local Moran I of -0.158074.



(a) LISA cluster map



(b) LISA significance map



(c) LISA scatterplot

Figure 24: Local Moran I statistic of prevalence in 2013 in Cameroon

A summary of the proximity of Cholera occurrences per region and the level of clustering determined using the Local Moran I Statistics can be seen in Table 4.

Year	Regions	Number of cases	Number of deaths	LISA	Significance
2004	Adamawa (LL)	√		-0.104763	0.01
2004	Adamawa (LL)		√	0.179367	0.01
2010	/	√		0.0891544	/
2010	/		√	0.0894443	/
2011	/	√		-0.0768258	/
2011	/		√	-0.113028	/
2012	Littoral (HH) and South (LH)	√		0.0945258	0.01
2012	Adamawa (LH), South West (LH), South (LH), East (LH) and Littoral (HH)		√	-0.0599206	0.01
2013	North West (HL) and South West (LH)	√		-0.221086	0.01and 0.05 respectively
2013	North (HH), Centre		√	0	0.01

	(HH), Adamawa (HH), North West (HH) , South West (HH), Littoral (HH), South (HH) and East (HH)				
Prevalence 2010	North (LH),Adamawa (HL) and South (LL)			-0.27967	0.01 and 0.05 respectively
Prevalence 2011	North (HL)			-0.05	0.01
Prevalence 2012	South (HL)			-0.280904	0.01
Prevalence 2013	North (HL)			-0.158074	0.01

Table 4: LISA and related statistics

5.5 Spatial Poisson Regression analysis

Poisson Regression analysis is used in this study to describe whether the count Cholera cases and deaths are predicted by the covariates (Table 5). This Poisson model is done in R free statistical software with the use of the Generalized Linear Model (GLM) function which is estimated via likelihood estimation. Poisson Regression has a number of extensions useful for count models (Cholera datasets) as the GLM is used to fit generalized linear models by specifying and by giving a symbolic description of the linear predictor and a description of the error distribution which allows us to model responses with distributions other than the Normal distribution, which is one of the assumptions underlying Linear Regression as used in many cases. The Poisson Regression fitted represents the change in response corresponding to a unit difference in a corresponding predictor (covariates).

Regions	Cho-cases	Cho deaths	Av Temp	Av Rain	DistStm km	Pop	Lat	Long
Extreme North	14025	836	21.6	780.7	-1	14481735	11	14.5
North	5391	346	21.7	1399.4	573	8687366	8.5	14
Adamawa	204	18	15.2	1314.6	-1	4245342	7.3	13.5
North West	144	9	15.3	2383.3	1619	7413206	6.3	10.5
South West	3496	60	19.3	2059.4	174	5694418	4.2	9.2
East	50	5	18.5	1512.5	743	3452807	4	14
South	417	16	20.4	1628.7	1278	2847208	2.5	11.75
Littoral	13853	201	23.1	3897.3	1980	11278109	4	20
West	2522	111	14.4	1784	1995	7332528	5.5	10.5

Centre	3634	147	19.4	1591.5	1965	14697064	4.8	12

Table 5: Variables for Spatial Poisson Regression analysis

For the purpose of this study, the Poisson command has been used to estimate a Poisson Regression model using the GLM function and executing the “summary” function in R statistical software. Total Cholera cases (Chocases) which is the response variable with its covariates; Average temperature (AvTemp), Average rainfall (AvRain), Distance to the nearest stream in kilometers (DistStmkm), Population (Pop), Latitude (Lat) and Longitude (Long) gives a Poisson Regression results of the total Cholera cases represented in Table 6.

Call: **GLM(formula = Chocases ~ -1 + AvTemp + AvRain + DistStmkm + Pop + Lat + Long, family = Poisson, data = Cholera)**					
Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
AvTemp	4.549e-01	8.037e-03	56.603	<2e-16	***
AvRain	-2.107e-04	2.651e-05	-7.947	1.91e-15	***
DistStmkm	6.930e-04	3.109e-05	22.289	<2e-16	***
Pop	4.015-08	3.641e-09	11.027	<2e-16	***
Lat	3.984e-01	9.984e-03	39.902	<2e-16	***
Long	-3.501e-01	1.378e-02	-25.410	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					
(Dispersion parameter for Poisson family taken to be 1)					
Null deviance: 702408.5 on 10 degrees of freedom					
Residual deviance: 7904.1 on 4 degrees of freedom					
coef(cases)					
AvTemp	AvRain	DistStmkm	Pop	Lat	Long
4.549248	-2.106706	6.929960	4.014993	3.983960	-3.500938

Table 6: Spatial Poisson Regression of total Cholera cases in 2004, 2010, 2011 and 2012 to June 2013

From the Spatial Poisson Regression of total Cholera cases in 2004, 2010, 2011 and 2012 to June 2013 (Table 6), the result represents a Poisson Regression coefficient for the total Cholera cases, standard error (std. Error) which are the standard errors of the individual regression coefficients, the z-value which is the ratio of the coefficient to the std. error of each respective predictor for the response (test statistics) and pr(>|z|) which are the p-values (SAS Annotated Output: Poisson Regression, STATA Annotated Output: Poisson Regression).

All coefficients are highly significant as Average temperature, Distance to nearest stream, Population and Latitudes are positively significant while Average rainfall and Longitude are negatively significant. Also the highly significance nature of the longitude and latitude indicates that the spatial coordinates are influencing the response variable. The result of the Poisson Regression shows that Average temperature, Average rainfall, Distance to the nearest streams in kilometers, Population, Latitude and Longitude are significant predictors of the number of Cholera cases in Cameroon. Since the coefficients of Average temperature, Distance to streams and Latitudes are positive, the expected number of Cholera cases increases with them. Also, the residual deviance is greater than the degree of freedom, meaning that the variance is not equal to the mean, thus, there is over dispersion.

The Spatial Poisson Regression of total Cholera deaths in 2004, 2010, 2011 and 2012 to June 2013 (Table 7), indicates that Population distribution is negatively significant only at 0.05 level while Average temperature, Distance to streams and Latitude have a positive significance level and Average rainfall and Longitude have a negative significance. Also the highly significance nature of the longitude and latitude indicates that the spatial coordinates are influencing the response variable. The residual deviance is greater than the degree of freedom, meaning that the variance is not equal to the mean, thus, there is over dispersion and a common cause is subject heterogeneity.

Call: **glm(formula = Chodeaths ~ -1 + AvTemp + AvRain + DistStmkm + Pop + Lat + Long, family = Poisson, data = Cholera)**					
Coefficients:					
	Estimate	Std. Error	z value	Pr(>|z|)	
AvTemp	4.365e-01	3.840e-02	11.365	< 2e-16	***
AvRain	-9.254e-04	1.272e-04	-7.274	3.49e-13	***
DistStmkm	1.229e-03	1.470e-04	8.363	< 2e-16	***
Pop	-2.878e-08	1.682e-08	-1.711	0.087	.
Lat	6.289e-01	4.837e-02	13.001	< 2e-16	***
Long	-5.835e-01	6.858e-02	-8.508	< 2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					
(Dispersion parameter for Poisson family taken to be 1)					
Null deviance: 17202.38 on 10 degrees of freedom					
Residual deviance: 121.01 on 4 degrees of freedom					
coef(deaths)					
AvTemp	AvRain	DistStmkm	Pop	Lat	Long
4.364501	-9.254329	1.229209	-2.878130	6.288673	-5.834935

Table 7: Spatial Poisson Regression of total Cholera deaths in 2004, 2010, 2011 and 2012 to June 2013

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Geographic information systems (GIS) have been used to perform the four basic functions of spatial input, storage, analysis and output (Goodchild 1987). This study utilized both the spatial and temporal statistical analytical methods to analyse raw data of count Cholera observed cases and deaths in 2004, 2010, 2011 and 2012 to June 2013 together with rainfall and temperature data. The proximity to digitized water sources to the ten main cities has been evaluated using GIS, and a Spatial Poisson Regression analysis was applied to investigate determining factors of Cholera cases and deaths. Results revealed that Cameroon has been seriously affected by Cholera epidemic in 2004, 2010, 2011 and 2012 to June 2013. Although the problems of underreporting have been encountered while exploring the datasets, areas of high population (Extreme North, Littoral, Centre and North) have encountered the highest number of count Cholera cases and deaths, and the highest hotspot was detected in the region of Littoral. Maps were produced to characterize the distribution of population, Cholera cases/deaths and environmental factors (rainfall and temperature). All datasets were integrated using a common platform in GIS (GeoDa, ArcMap 10.1 and R statistical software). All objectives and research questions of this study are addressed below.

Objective 1: To examine health problems such as Cholera as a consequence of climate variability.

- **Research question 2**: "What are the underlying risk factors?"

Rainfall and temperature extremes in the dry and rainy seasons influence Cholera. North West, South West, Littoral and South regions experience the highest rainfall while Extreme North, North, Adamawa, East, West, and Centre regions experience the lowest rainfall (Figure 10). Areas with the highest temperatures are Extreme North, North, Adamawa, Centre and Littoral regions while low temperatures are experienced in the North West, South West, West and East (Figure 11). The areas most affected with Cholera Epidemic are Extreme North (2010 and 2011), Littoral (2004 and 2011) and North (2011) regions (Figure 8). Therefore both the dry and wet seasons have potential factors to stimulate *V. Cholerae* multiplication and consequently Cholera Epidemic and the positive association of Cholera to rainfall and temperature can be used in forecasting Cholera outbreak in Cameroon.

Objective 2: To investigate the patterns of Cholera cases and deaths over time in 2004, 2010, 2011 and 2012 to June 2013.

- **Research question 1**: Are there higher risk of Cholera in some regions?"

In this study, Cholera epidemic was examined in 2004, 2010, 2011 and 2012 to June 2013 (Figure 8 and 9), with 2011 exhibiting the highest epidemic year. The yearly patterns of high Cholera count cases with low death (Figure 12) are visualised in the South West (2011), Littoral (2004 and 2011) and Centre (2011) regions. High Cholera count cases and high deaths are seen in the Extreme North (2010 and 2011) and North (2011) regions. Therefore it can be concluded that these regions have the highest risk to potential Cholera epidemic.

Objective 3: To map potential Cholera causing factors such as water reservoirs using GIS in Cameroon.

- **Research question 5**: "Can the proximity distance to the nearest waterbodies influence pollution?"

Water reservoirs were obtained, digitized and mapped in ArcMap 10.1 and the NEAR function was used to obtain proximity distances from the nearest waterbodies to the ten main cities (centroids) in Cameroon. Closest water reservoir proximity to the main towns were obtained in the North, South West and East regions and farthest water proximity was in the Littoral, West, Centre, Extreme North and Adamawa (Table 3). The most affected by the Cholera Epidemic are the Extreme North, Littoral and North regions (Figure 8). There is a possibility of contamination in the areas with the closest proximity and also evidence of the consumption of unsterilized water sources like bore holes in the areas farthest in proximity. Therefore, the existing fresh water consumption within the country is a catalyst to Cholera epidemic.

Objective 4: To outline and propose possible solutions to the effects of Cholera Epidemics (based on epidemiological data) for future health analysis and for health officials and policy makers.

A number of possible solutions such as sanitation, sterilization of water before consumption, controlling illegal refuse dumps especially close to fresh waterbodies which can lead to water reservoir contamination and the supply of pipe borne water connectivity to all rural and urban areas of the country can reduce the effects of climatic variability and guarantee a purified water consumption system to all inhabitants.

Research question 3: "Is there underreporting of Cholera by region and by year?"

There is evidence of underreporting on raw datasets collected from the Ministry of Public Health in Cameroon on Cholera observation (count cases and deaths). These datasets either gave the Cholera affected numbers for the whole of Cameroon or counts that can only be grouped into the ten main regions of Cameroon without reporting on the level of the 58 districts which makes the area of sampling large and the assumptions, analysis and results finalized only at the level of the regions, which is insufficient to detect the main districts mostly affected.

Research question 4: "Does Cholera turn to occur in proximity to each region and is there a level of clustering around a particular region?"

Examining Cholera Epidemic in Cameroon using the Local (Anselin) Moran I statistics, it was found that Cholera turn to occur in proximity to each region. In 2004 there was a Low-Low (LL) clustering in the Adamawa region (Moran I = -0.104763, p = 0.01). In 2010 (Moran I = 0.0891544) and 2011 (Moran I = -0.0768258) no level of clustering was produced. In 2012, there was a Low-High (LH) negative spatial autocorrelation in the South region and a High-High clustering in the Littoral region (Moran I = 0.0945258, p = 0.01). From January to June 2013, there was a Low-High (LH) negative spatial autocorrelation in the South West region and a High-Low (HL) negative spatial autocorrelation in the North West region (Moran I = -0.221086, p = 0.05 and 0.01 respectively)

Furthermore, the prevalence (cases/population) from 2010 to June 2013 gave a Low-Low (LL) cluster in the South region, a Low-High (LH) negative spatial autocorrelation in the North region and a High-Low (HL) negative autocorrelation in the Adamawa region (Moran I = -0.27967, p = 0.01 in the North region and 0.05 in the South and Adamawa regions) in 2010. In 2011, there was a High-Low (HL) negative spatial autocorrelation in the North region (Moran I = -0.05, p = 0.01), 2012 visualized a High-Low (HL) negative spatial autocorrelation in the South region (Moran I = -0.280904, p = 0.01) and January to June 2013 illustrate a High-Low (HL) negative spatial autocorrelation in the North region (Moran I = -0.158074, p = 0.01) as summarised in Table 4.

Finally, the Poisson Regression results indicate that the coefficient of the covariates to Cholera cases is 4.55 (Average temperature), -2.11 (Average rainfall), 6.93 (Distance to the nearest stream), 4.02 (Population distribution), 3.98 (Latitude) and -3.50 (Longitude). Furthermore, the coefficient of the covariates to Cholera deaths is 4.36 (Average temperature), -9.25 (Average rainfall), 1.23 (Distance to the nearest stream), -2.88 (Population distribution), 6.29 (Latitude) and -5.83 (Longitude). Therefore climatic factors, proximity to fresh waterbodies, population and the highly significance nature of the longitude and latitude are among the factors that instigate Cholera Epidemic in Cameroon.

6.2 Limitations of the study

All of the Cholera datasets from 1971 to 1998 provide data aggregated for the whole of Cameroon. From 1999 to June 2013 there are many missing districts and regions datasets for which the count Cholera cases and deaths were collected.

Also, there is underreporting of Cholera cases at the level of the 58 Districts in Cameroon and all of the conclusions can only be made at the level of the ten regions without indicating the particular districts within a region giving a high or low Cholera count cases/deaths and most of the datasets (Cholera data) were difficult to obtain.

Rainfall and Temperature datasets from the meteorological stations ended in 2007, therefore, it is not up to date leading the yearly measurements on rainfall and temperature obtained in 2004, 2010, 2011 and 2012 to June 2013 not to be properly analysed yearly.

The government of Cameroon (Ministry of health) needs to start collecting Cholera information on the level of the 58 district because these results can be greatly improved if the Cholera cases/deaths were obtained for the 58 Districts of Cameroon.

Due to this factor, the influence of the covariates can be seen only at the level of the ten regions but now the particular Districts most affected from Cholera epidemic cannot be distinguish from the less affected Districts.

6.3 Future studies

It is good to get up to date high resolution satellite imagery and conduct an image classification for the ten regions to get the present status of the waterbodies found in Cameroon.

Using up to date rainfall and temperature datasets to conduct the same study if available will help improve this study.

Future studies should include the use of a high resolution imagery to detect refuse dump sites within Cameroon and also calculate its proximity to the nearest cities and waterbodies which can influence water pollution and potential contamination.

Also it will be good to use Cholera datasets available for the 58 Districts of Cameroon to improve this study. Conducting Local (Anselin) Moran I and doing disease mapping using Poisson Regression for all the 58 Districts to get the particular district being affected the most by Cholera Epidemic.

BIBLIOGRAPHIC REFERENCES

"SPATIAL AUTOCORRELATION" *GIS Dictionary* 2011. http://support.esri.com/en/knowledgebase/GISDictionary/term/spatial%20autocorrelation(12 November, 2013).

ANSELIN, L., SYABRI, I., KHO, Y., 2006, *GeoDa: An Introduction to Spatial Data Analysis*. Geographical Analysis 38 (1), 5-22.

ANSELIN, L., 2005, *Exploring Spatial Data with GeoDa™: A Workbook*, Copyright © 2004-2005 Luc Anselin, All Rights Reserved, (URL:https://geodacenter.asu.edu/system/files/geodaworkbook.pdf).

ANSELIN, L., 2010, "*Local Indicators of Spatial Association – LISA*," Geographical Analysis, Volume 27, Issue 2, page 98, (URL:http://onlinelibrary.wiley.com/doi/10.1111/j.1538-4632.1995.tb00338.x/pdf).

BARRATT, H. M. K., 2009, *Epidemic Theory (effective and basic reproduction numbers, epidemic thresholds) and techniques for infectious disease data (construction and use of epidemic curves, generation numbers, exceptional reporting and identification of significant clusters)* (URL:http://www.healthknowledge.org.uk/public-health-textbook/research-methods/1a-epidemiology/epidemic-theory).

BOMPANGUE, D., VESENBECKH, S. M., GIRAUDOUX, P., CASTRO, M., MUYEMBE, J. J., ILUNGA, B. K., MURRAY, M., 2012, *Cholera ante portas- The re-emergence of Cholera in Kinshasa after a ten-year hiatus*, Version 2. PLoS Curr. 2012 February 17 [revised 2012 March 12]; 4: RRN 1310, (URL:http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3299488/#__ffn_sectitle)

BORROTO, R. J., MARTINEZ-PIEDRA, R., 2000, *Geographical Patterns of Cholera in Mexico, 1991-1996*, International Journal of Epidemiology 2000; 29:764-772, (URL: http://ije.oxfordjournals.org/content/29/4/764.full.pdf+html).

BOULOS, M. N. K., 2005, *Web GIS in practice III: creating a simple interactive Map of England's Strategic Health Authorities using Google Maps API, Google*

Earth KML, and MSN Virtual Earth Map Control, © 2005 Boulos; Licensee BioMed Central Ltd. (URL: http://www.ij-healthgeographics.com/content/4/1/22).

CDC, 2012, *Centers for Disease Control and Prevention, Principles of Epidemiology in Public Health* Practice, 3rd Edition (URL:http://www.cdc.gov/osels/scientific_edu/ss1978/lesson1/section11.html).

CHINGAYIPE, E. M., 2008, *Factors affecting Cholera Case Detection by the Communities in Chiradzulu District*. Master's dissertation, College of Medicine Malawi.

COLLINS ENGLISH DICTIONARY, 2000, 5th Edition first published in © HarperCollins Publishers 1979, 1986, 1991, 1994, 1998, 2000 and Collins A-Z Thesaurus 1st edition first published in 1995 © HarperCollins Publishers 1995.

EMCH, M., FELDACKER, C., YUNUS, M., STREATFIELD, P. K., DINHTHIEM, V., CANH, D. G., ALI, M., 2008, *Local Environmental Predictors of Cholera in Bangladesh and Vietnam*, copyright © 2008 by The American Society of Tropical Medicine and Hygiene, Am. J. Trop. Med. Hyg., 78 (5), 2008, pp.823-832.

ESRI (Environmental Systems Resource Institute). 2012. ArcMap 10.1. ESRI, Redlands, California.

FERNANDEZ, M. A. L., SCHOMAKER, M., MASON, P. R., FESSELET, J. F., BAUDOT, Y., BOULLE, A., MAES, P., 2012, *Elevation and Cholera: an Epidemiological Spatial Analysis of the Cholera Epidemic in Harare, Zimbabwe, 2008-2009*, © 2012 Luque Fernandez et al.; Licensee BioMed Central Ltd, (URL: http://www.biomedcentral.com/1471-2458/12/442/).

FRERICHS, R. R., 2013, Cholera in Haiti and the modern "John Snow", Epilogue of the Origin of Cholera in Haiti. Department of Epidemiology, University of California, Los Angeles (UCLA), (URL:http://www.ph.ucla.edu/epi/snow/Cholera_haiti.html).

GAFFGA, N. H., TAUXE, R. V., MINTZ, E. D., 2007, *Cholera: A New Home in Africa?*, copyright © 2007 by Am. J. Trop. Med. Hyg., 77 (4), 2007, pp.705-713.

GEOHIVE - © GeoHive, 2000-2013 (URL:http://www.geohive.com/cntry/cameroon.aspx)

GLOBAL GAZETTEER VERSION 2.2. *Directory of Cities, Towns, and Regions in Cameroon*, (URL: http://www.fallingrain.com/world/CM/).

GOODCHILD, M, F., 1987, *A Spatial Analytical Perspective on Geographical Information Systems*, Int. J. Geographical Information Systems, 1987, Vol.1, No.4, 327-334, (URL: http://www.geog.ucsb.edu/~good/papers/95.pdf).

HIJMANS, R. J., CRUZ, M., ROJAS, E., GUARINO, L., DIVA-GIS. *A Geographic Information System for the Management and Analysis of Genetic Resources Data*.

JENNIFER, L., 2009, *Spatial Autocorrelation Statistics*, © Jennifer Lentz 2009, (URL: http://jenniferalentz.info/Teaching/StudyGuides/SpatialAutocorrelation.pdf)

JUTLA, A. S., AKANDA, A. S., GRIFFITHS, J. K., COLWELL, R., ISLAM, S., 2011, *Warming Oceans, Phytoplankton, and River Discharge: Implication for Cholera Outbreaks*, copyright © 2011 by, Am. J. Trop. Med. Hyg., 85 (2), 2011, pp. 303-308, (URL: http://www.ajtmh.org/content/85/2/303.full).

KOMETA, S. S., EBOT, M. A., NGALA, H. N., SANI, G. A., 2013, *Human Health Vulnerability to Climate Variability: The Cases of Cholera and Meningitis in Cameroon*, Copyright © Canadian Center of Science and Education, Vol.5, No.1, 2013 ISSN 1916-9779 E-ISSN 1916-9787.

KRIEGER, N., WATERMAN, P., LEMIEUX, K., ZIERLER, S., HOGAN, J. W., 2001, *On the Wrong Side of the Tracts? Evaluating the Accuracy of Geocoding in Public Health Research*, Am. J. Public Health. 2001; 91:1114–1116, (URL:http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1446703/pdf/11441740.pdf).

KUMMU, M., DE MOEL, H., WARD, P. J., VARIS, O., 2011, *How Close Do We Live to Water? A Global Analysis of Population Distance to Freshwaterbodies*. PLoS ONE 6(6): e20578. doi: 10.1371/journal.pone.0020578. (URL:http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0020578).

LIPP, K. E., HUQ A., COLWELL, R. R., 2002, *Effects of Global Climate on Infectious Disease: The Cholera Model*, Clinical Microbiology Review. October 2002; 15:757-770, doi: 10.1128/CMR.15.4.757-770, (URL:http://cmr.asm.org/content/15/4/757.full).

LOZANO-FUENTES, S., ELIZONDO-QUIROGA, D., FARFAN-ALE, J. A., LOROÑO-PINO, M. A., GARCIA-REJON, J., GOMEZ-CARRO, S., LIRA-ZUMBARDO, V., NAJERA-VAZQUEZ, R., FERNANDEZ-SALAS, I., CALDERON-MARTINEZ, J., DOMINGUEZ-GALERA, M., MIS-AVILA, P., MORRIS, N., COLEMAN, M., MOORE, C. G., BEATY, B, J., EISEN, L., 2008, *Use of Google Earth^{TM} to strengthen Public Health Capacity and Facilitate Management of Vector-borne Diseases in Resource-poor Environments*, Bull World Health Organ vol.86 No.9 Genebra Sep.2008, (URL:http://www.scielosp.org/scielo.php?pid=S0042-96862008000900016&script=sci_arttext).

MAGNY, G. C., MURTUGUDDE, R., SAPIANO, M. R. P., NIZAM, A., BROWN, C. W., BUSALACCHI, A. J., YUNUS, M., NAIR, G. B., GIL, A. I., LANATA, C. F., CALKINS, J., MANNA, B., RAJENDRAN, K., BHATTACHARYA, M. K., HUQ, A., SACK, R. B., COLWELL, R. R., 2008, *Environmental Signatures Associated with Cholera Epidemics*. Contributed by Rita R. Colwell, September 26, 2008 (received for review August 1, 2008), vol. 105 No.46, Guillaume Constantin de Magny, 17676–17681, (URL:http://www.pnas.org/content/105/46/17676.full).

MAHAMUD, A. S., AHMED, J. A., NYOKA, R., AUKO, E., KAHI, V., NDIRANGU, J., NGUHI, M., BURTON, J. W., MUHINDO, B. Z., BREIMAN, R. F., EIDEX, R. B., 2012, *Epidemic Cholera in Kakuma Refugee Camp, Kenya, 2009: the Importance of Sanitation and Soap*, copyright © 2012 Mahamud et al. J. Infect Dev Ctries 2012, 6 (3): 234-241.

MAYALA, B. K., MBOERA, L. E. G.,GWACHA, F., 2003, *Mapping of Cholera Risks using Geographical Information System in IIala District, Tanzania*, Tanzania Health Research Bulletin (2003), Vol.5, No.1, (URL:http://www.ajol.info/index.php/thrb/article/view/14197/15902).

MCLEOD, K. S., 2000, *Our sense of Snow: the Myth of John Snow in Medical Geography*, copyright © 2000 Elsevier Science Ltd, Social Science & Medicine 50 (2000) 923-935, (URL:http://urizen-geography.nsm.du.edu/~psutton/AAA_Sutton_WebPage/Sutton/Courses/Geog_4020_Geographic_Research_Methodology/Course_Documents/Seminal_Papers_Geography/snow_medical_geography.pdf).

NDOUGSA, M. T., 2009, Republic of Cameroon, *Cameroon Geological setting*, Ministry in charge of Mines and Geology.

NEBA, A., 1999, *Modern Geography of the Republic of Cameroon*, 3rd ed. Bamenda: Neba Publishers.

NJOH, E. M., 2010, *The Cholera Epidemic and Barriers to Healthy Hygiene and Sanitation in Cameroon*: A protocol Study. Umea Universitet.

NYAMOGOBA, H. D. N., OBALA, A. A., KAKAI, R., 2002, Combating Cholera Epidemic b Targeting Reservoirs of Infection and Transmission Routes: A Review, East African Medical Journal Vol.79 No.3, (URL:http://www.ajol.info/index.php/eamj/article/view/8896/1792).

OSEI, F. B., 2010, *Spatial Statistics of Epidemic Data: The Case of Cholera Epidemiology in Ghana*. PHD dissertation, Faculty of Geo-Information Science and Earth and Observation, University of Twente, copyright © 2010 by Osei Frank Badu.

OSEI, F. B., DUKER, A. A., 2008, *Spatial Dependency of V. Cholera Prevalence on Open Space Refuse Dumps in Kumasi, Ghana: A Spatial Statistical Modeling*, copyright © Osei and Duker; Licensee BioMed Central Ltd. International Journal of Health Geographics, Vol.7, (URL:http://www.ij-healthgeographics.com/content/7/1/62).

PIARROUX, R., FAUCHER, B., 2012, Cholera Epidemic in 2010: *Respective Roles of Environment, Strain changes, and Human-driven Dissemination*, copyright © 2012 European Society of Clinical Microbiology and Infection, CMI, 18, 231-238.

REYBURN, R., RYUN, D., EMCH, M., KHATIB, A., SEIDLEIN, L., ALI, M., 2011, *Climate Variability and the Outbreaks of Cholera in Zanzibar, East Africa: A Time Series Analysis*, copyright © 2011 by The American Society of Tropical Medicine and Hygiene, Am. J. Trop. Med. Hyg., 84 (6), 2011, pp. 862-869, (URL:http://www.ncbi.nlm.nih.gov/pubmed/21633020).

RICHARDS, T. B., CRONER, C. M., RUSHTON, G., BROWN, C. K., FOWLER, L., 1999, *Geographic Information Systems and Public Health: Mapping the Future*, Public Health Rep. 1999 Jul-Aug; 114(4): 359–373, (URL:http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1308497/).

SAS Annotated Output: Poisson Regression, (URL:http://www.ats.ucla.edu/stat/sas/output/sas_poisson_output.htm).

SASAKI, S., SUZUKI, H., IGARASHI, K., TAMBATAMBA, B., MULENGA, P., 2008, *Spatial Analysis of Risk Factor of Cholera Outbreak for 2003-2004 in a Peri-urban Area of Lusaka, Zambia*, copyright © 2008 by The American Society of Tropical Medicine and Hygiene, Am. J. Trop. Med. Hyg., 79 (3), 2008, pp. 414-421, (URL:http://public.beuth-hochschule.de/~kred/Literatur/GIS_Med_Geo/PDF/Sasaki_et_al_2008-1744621058/Sasaki_et_al_2008.pdf).

SCOTCH, M., PARMANTO, B.,GADD, C. S., SHARMA, R. K., 2006, *Exploring the role of GIS during Community Health Assessment Problem Solving: Experiences of Public Health Professionals*, Int. Journal of Health Geographics 2006, 5:39, doi: 10.1186/1476-072X-5-39, (URL:http://www.ij-healthgeographics.com/content/5/1/39).

SHAPIRO, R. L., OTIENO, M. R., ADCOCK, P. M., PHILLIP-HOWARD, P. A., HAWLEY, W. A., KUMAR, L., WAIYAKI, P., NAHLEN, B. L., SLUTSKER, L., 1999, *Transmission of Epidemic Vibrio Cholera 01 in Rural Western Kenya Associated with Drinking Water from Lake Victoria: An Environmental Reservoir for Cholera?*, copyright © 1999 by The American Society of Tropical Medicine and Hygiene, Am. J. Trop. Med. Hyg., 60 (2), 1999, pp. 271-276.

SHITTU, O. B., AKPAN, I., POPOOLA, T. O. S., OYEDEPO, J. A., OGUNSHOLA, E. O., 2010, *Epidemiological Features of a GIS-supported Investigation of Cholera Outbreak in Abeokuta, Nigeria*, Journal of Public Health and Epidemiology Vol.2(7), pp.152-162, (URL:http://www.academicjournals.org/JPHE/PDF/pdf2010/October/Shittu%20et%20al.pdf).

SHULTZ, A., OMOLLO, J. O., BURKE, H., QASSIM, M., OCHIENG, J. B., WEINBERG, M., FEIKIN, D. R., BREIMAN, R. F., 2009, *Cholera Outbreak in Kenyan Refugee Camp: Risk Factors for Illness and Importance of Sanitation*, copyright © 2009 by The American Society of Tropical Medicine and Hygiene, Am. J. Trop. Med. Hyg., 80 (4), 2009, pp. 640-645.

STATA Annotated Output: Poisson Regression, (URL:http://www.ats.ucla.edu/stat/stata/output/stata_poisson_output.htm).

TRAERUP, S. L. M., ORTIZ, R. A., MARKANDYA, A., 2010, *the Health Impacts of Climate Change: A Study of Cholera in Tanzania. Basque Centre for Climate Change (BC3)*, Bilbao, working Paper Series 2010-01.

WHO - WORLD HEALTH ORGANIZATION 2012, Global Task Force on Cholera Control, Prevention and control of Cholera outbreaks: *WHO Policy and Recommendations*, Fact sheet N°107, (URL:http://www.who.int/mediacentre/factsheets/fs107/en/).

Masters
Program
in **Geospatial**
Technologies

Supported by:

Education and Culture

ERASMUS MUNDUS